ANNÉE 2017

THÈSE / UNIVERSITÉ DE RENNES 1
sous le sceau de l'Université Bretagne Loire

pour le grade de

DOCTEUR DE L'UNIVERSITÉ DE RENNES 1

Mention : Sciences Économiques

École doctorale Sciences de l'Homme des Organisations et de la Société (SHOS)

Ewen Gallic

Préparée à l'unité de recherche CREM (UMR CNRS 6211)
Centre de Recherche en Économie et Management
Faculté de Sciences Économiques

Climate Change and Agriculture

Thèse soutenue à Rennes le 2 Juin 2017

devant le jury composé de :

Jean-Paul Chavas
Anderson-Bascom Professor, University of Wisconsin
Rapporteur

Alban Thomas
Directeur de recherche, INRA, Toulouse School of Economics
Rapporteur

Pascale Combes Motel
Professeur, Université d'Auvergne
Examinateur

Jean-Christophe Poutineau
Professeur, Université de Rennes 1
Examinateur

Katheline Schubert
Professeur, Paris School of Economics, Université Paris 1 Panthéon–Sorbonne
Examinateur

Catherine Benjamin
Professeur, Université de Rennes 1
Directrice de thèse

Around the world, climate change is an existential threat – but if we harness the opportunities inherent in addressing climate change, we can reap enormous economic benefits

Ban Ki-moon, April 2014

Remerciements

Comme le veut la coutume, j'aimerais remercier ceux qui ont participé de près ou de loin à l'aboutissement de ce travail. Cet exercice me semble difficile, non pas par absence de reconnaissance, bien au contraire, mais par crainte d'oublier de mentionner ceux qui m'ont accompagné au long de ces dernières années. À ceux-là, je demande de bien vouloir me pardonner.

Tout d'abord, je tiens à faire part de ma profonde reconnaissance à Catherine Benjamin, qui a accepté d'encadrer cette thèse. Merci Catherine pour tous vos conseils, votre soutien et pour la confiance placée en moi.

Merci à Jean-Paul Chavas, Alban Thomas, Pascale Combes-Motel, Jean-Christophe Poutineau et Katheline Schubert de m'avoir fait l'honneur d'être membre du jury de cette thèse.

Ma reconnaissance va à Isabelle Cadoret et Valérie Monbet, qui ont toutes deux permis à cette thèse de débuter.

Je remercie l'école doctorale SHOS, ses présidents Franck Moraux et Jean-René Binet, ainsi que ses gestionnaires Alexandrine Belin Brunel et Pasquale Breger, pour le cadre de formation.

Le CREM m'a offert un excellent cadre de travail. Je tiens à exprimer ma reconnaissance aux directeurs actuel et passés du laboratoire, Yvon Rocaboy, Vincent Merlin et Franck Moraux, ainsi qu'à leurs représentants de la place Hoche, Fabien Moizeau et David Masclet. L'environnement proposé par le CREM m'a permis de rencontrer des personnes formidables. J'ai une pensée particulière pour Marie-Hélène Hubert grâce à qui j'ai eu la chance d'assister à de nombreux séminaires très enrichissants en économie environnementale, et grâce à qui j'ai pu participer à des groupes de travail et conférences. Parmi les nombreuses personnes passionnantes et passionnées croisées au sein du CREM, j'aimerais également adresser ma reconnaissance à Olivier L'Haridon, pour son expertise, sa bienveillance, ainsi que ses regards éclairés sur le monde. Je n'oublierai jamais la conversation que nous avons eue face au vent glacial alpin à propos de la générosité, et espère pouvoir en appliquer le contenu tout au long de ma vie. J'ai une pensée pour Elven Priour, "l'éternel doctorant". Le laboratoire ne pourrait fonctionner sans tous ses membres administratifs, que je salue également pour leur professionnalisme et leur efficacité : Anne l'Azou, Hélène Coda-Poirey, Julie Le Diraison, Cécile Madoulet, Daniele Moret-Bailly.

Mon parcours est étroitement lié à l'Université de Rennes 1, qui après m'avoir formé jusqu'au Master, m'a accordé une allocation de recherche puis un contrat d'ATER. Je salue l'ensemble des enseignants qui m'ont transmis leurs connaissances depuis mes deux premières années jusqu'au master. En particulier, je souhaite remercier celles et ceux qui m'ont aiguillé lors de mon changement d'orientation de l'informatique vers l'économie et les statistiques, à savoir Nathalie Colombier, Sophie Larribeau, et Raphaël Suire. Il me serait impossible de ne pas adresser ma sympathie à Chantal Guéguen qui aura toujours veillé à me proposer un service compatible avec un emploi du temps partagé entre la recherche et l'enseignement, tout en me proposant une variété dans les enseignements. Merci également à Thierry Karcher pour les TDs de statistique. Un grand merci à Alice Bernard pour la relecture de l'introduction.

Qu'on me permette de mentionner la bienveillance de l'équipe administrative de la Faculté de Sciences Économiques : Aurélie Allais, Muriel Benoist, Marc Borsatto, Annick Bougeant, Sylvie Bourset, Karine Bulourde, Jocelyne Camilleri, Sylvie Chanteux, Gilles Conan, Karine Cousin, Nadine Desodt, Angélique Dubois, Fabienne Ealet, Maddy Helou, Lean-Louis Le Fessant, Marie-France Lechesne, Caroline Lemoine, Sylvie Lorho-Chevalerias, Yvelise Maret, Soizic Masson, Françoise Mazzoleni, Jean-Willy Mbuko, Jamele Mezali, Denis Noël, Carine Philippot, Annie Quéméré, Corinne Rémondin, Clarisse Turuban, Christèle Viel et Annie Vignon.

Je songe également avec reconnaissance à tous les employés du restaurant universitaire qui m'ont nourri pendant plusieurs années, six jours sur sept, parfois midi et soir. Merci à Claudine, Fred & Fred, Jean-Yves, Isabelle, Laurence, Lionnel et Nathalie. Vos sourires quotidiens m'ont transmis une belle énergie.

Je souhaite remercier mes co-auteurs pour leurs discussions fructueuses. Merci à François Briatte, dont la capacité à travailler sans relâche sur de nombreux sujets plus intéressants les uns que les autres m'inspire. Un grand merci à Jean-Christophe Poutineau, qui m'impressionne par la clarté avec laquelle il parvient à poser un cadre d'analyse rigoureux, permettant d'atteindre sans peine un résultat final précis. Ses éclairages sur la recherche, sur le monde universitaire comme sur le monde de la musique m'honorent, et je lui suis très reconnaissant pour toute l'aide qu'il a pu m'apporter.

I would also like to thank all the participants of the seminars, workshops and conferences for their helpful comments and suggestions, in particular, Stéphane Adjemian, Zouhair Ait Benhamou, Dorothée Charlier, Pascale Combes Motel, Jean-Louis Combes, Jean-Charles Garibal, Frédéric Karamé, Robert Kollmann, François Langot, Mengdi Liu, Jean-Christophe Poutineau, Tovonony Razafindrabe, Christophe Tavéra, Christian Traeger, Roland C. Winkler, Stefanos Xenarios.

Parmi toutes les personnes qui m'ont accompagné durant cette aventure, il en est une dont le nom pourrait figurer dans la plupart des paragraphes précédents, celui d'Arthur Charpentier. Je ne sais par où commencer pour le remercier, tellement je lui suis reconnaissant et redevable. Merci pour tous les conseils, les discussions, les travaux de recherche, les séminaires, les cours, les projets et les personnes que tu m'as fait rencontrer. Je te dois beaucoup et ne saurai jamais assez te témoigner ma gratitude.

La thèse est une formidable aventure humaine, durant laquelle j'ai partagé de nombreux moments mémorables avec l'ensemble des doctorants et membres de l'association PROJECT, notamment Guillaume Beaurain, Henri Busson, Thibaud Cargoët, Thomas Cadet, Clément Dheilly, Nicolas Gavoille, Charles Hamon, Ons Jedidi, Maxime Lamandé, Gabin Langevin, Thao Nguyen, Emmanuel Peterle, Guillaume Queffelec, Siriki Coulibaly, Zhang Jiang. J'adresse une pensée à mes trois amis des bureaux 104 et 108, pour qui le mot “solidarité” prend tout son sens. May Atef Aly Sayd Ahmed Attallah, Romain Gaté et Thi Thanh Xuan Tran ; c'est un privilège d'avoir passé tant de temps à vos côtés. Puisse notre amitié perdurer au-delà de cette thèse. J'ajoute un mot spécialement destiné à Xuan, pour la remercier de tout ce qu'elle a pu me raconter sur le Vietnam, et pour toutes les rencontres avec la communauté, notamment avec Uyen Tran. *Last but not least*, mes pensées s'adressent aux membres de mon premier bureau, Gauthier Vermandel et Pascaline Vincent, avec qui j'ai sûrement passé les meilleures années de ma vie. Je suis persuadé que nos routes n'en finiront pas de se croiser, et que nous saurons préserver ces liens d'amitié. Merci de votre soutien. Gauthier, merci énormément pour tous tes encouragements, pour ta mansuétude, et pour l'exemple que tu donnes. Tout ce que tu as fait pour moi restera gravé dans ma mémoire.

Mes pensées vont enfin à mes amis et ma famille. Alexis, Célia, Hicham, Isabelle & Kévin, Jacqueline, Jérôme, Julien-Yacine, Martin, Stéphanie & Laurent, Sonia. Je songe à vous et vous suis reconnaissant d'avoir supporté mes enthousiasmes comme mes découragements. Enfin, je souhaite remercier du fond du cœur ma famille, qui n'aura eu de cesse de me soutenir. Merci à Henri, pour sa grande compréhension, et mes excuses pour le peu de temps passé avec lui. J'ai une pensée pour Éliane, qui par sa force m'aura inspiré à de nombreuses reprises pour surmonter les obstacles. Je remercie ma mère et mon père d'avoir évité de me poser l'éternelle question adressée aux doctorants : "*Et la thèse, ça avance ?*" et d'avoir plutôt formulé leur infaillible soutien par l'emploi des mots suivants : "*On ne te demande pas où tu en es rendu, mais on pense bien à toi*". Merci à tous les deux, pour votre amour indéfectible. Il me reste une personne à remercier, Claire, ma sœur, qui ne cessera d'être l'exemple que j'essaie de suivre, et sans laquelle je n'aurais sûrement jamais suivi de cours d'économie.

Contents

Résumé en français

La fin de l'année 2015 a été marquée par la vingt-et-unième Conférences des Parties de la Convention cadre des Nations unies sur les changements climatiques. Cette conférence a réuni les représentants de 195 nations afin de prendre des mesures pour lutter contre le changement climatique. Ce réchauffement, à en croire l'accumulation des preuves scientifiques, serait principalement dû à une augmentation de la concentration en gaz à effet de serre, résultant notamment des activités humaines. Bien que des effets positifs consécutifs à ce réchauffement pourraient être ressentis dans certaines parties du monde, un grand nombre d'études indique qu'ils seraient compensés à l'échelle globale par les effets négatifs ressentis dans les autres régions, faisant *de facto* peser une grave menace sur l'avenir de notre planète. Les attentes de la Conférence des Nations Unies sur les changements climatiques étaient par conséquent élevées. Les chefs de file mondiaux, y ont exprimé leur volonté de la nécessité d'agir pour éviter les effets les plus catastrophiques du changement climatique. Les signataires du traité rédigé lors de cette conférence ont convenu qu'il était nécessaire de limiter le réchauffement climatique en dessous d'un seuil d'une augmentation de 2 degrés Celsius par rapport à l'aire pré-industrielle, avec une volonté de mener des efforts encore plus poussés pour limiter cette augmentation en-dessous de $1,5$ degrés Celsius. L'accord, ratifié par 142 pays, est entré en vigueur moins d'un an plus tard, en novembre 2016.

De manière implicite, les signataires de l'accord de Paris ont reconnu qu'en-deçà d'une augmentation de la température globale de 2 degrés Celsius par rapport aux niveaux pré-industriels, l'humanité pourrait s'adapter aux nouvelles conditions climatiques. Toutefois, les moyens mis en œuvre afin de parvenir à respecter l'accord climatique ainsi que les coûts sous-jacents sont accompagnés d'une forte incertitude. En fait, les coûts financiers du changement climatique représentent un problème économique ayant donné lieu à de nombreuses études scientifiques. Non seulement la littérature s'attache à estimer les coûts liés à la mise en place de politiques d'atténuation, mais elle tente également d'évaluer les coûts de l'inaction (OECD, 2015).

Une manière populaire d'évaluer ces coûts a été introduite par Nordhaus (1994). Il s'agit d'une approche globale qui consiste à représenter le monde à l'aide d'équations mathématiques. L'idée est d'introduire une fonction de dommage climatique venant perturber l'économie. Cette fonction de dommage lie l'augmentation de la température au PIB, la température étant elle-même fonction du niveau de concentration en gaz à effet de serre. Les modèles mathématiques alors construits peuvent ensuite être utilisés pour évaluer les bénéfices de la mise en place de certaines actions visant à limiter l'émission des gaz à effet de serre (voir, p. ex., Hope et al., 1993 ; Tol, 2005). Toutefois, il n'existe pas de réponse tranchée quant à la meilleure manière de s'attaquer à la diminution des émissions de gaz à effet de serre. Certains auteurs recommandent d'agir rapidement (p. ex., Stern, 2007) tandis que d'autres suggèrent une approche plus progressive (p. ex., Nordhaus, 2007) impliquant moins de contrôles dans le présent et en faveur d'un report de l'action dans le futur.

Cette approche globale pour mesurer les impacts du changement climatique est complétée dans la littérature par une multitude d'approches partielles, qui se concentrent sur un secteur économique particulier. Parmi ces secteurs économiques, l'agriculture est un champ d'application privilégié, du fait de sa forte dépendance au conditions climatiques. De manière étonnante, l'agriculture n'est pas directement mentionnée dans les accords de Paris de 2015. Les impacts potentiels du changement climatique sur ce secteur, malgré la faible importance relative de l'agriculture dans le PIB mondial, posent pourtant de nombreux défis et menaces sur l'avenir de notre planète (OECD, 2015), particulièrement à l'égard de la sécurité alimentaire.

Un large pan de la littérature est ainsi dédié à l'étude des relations entre l'agriculture et le climat, à commencer par de nombreuses études simulant la croissance des céréales à l'aide de modèles mathématiques (voir, p. ex., Ritchie and Otter, 1985 ; Jones et al., 1986 ; Brisson et al., 1998). En associant ces modèles à d'autres visant à simuler des conditions climatiques, il est possible d'estimer les effets potentiels du changement climatique sur la sécurité alimentaire (voir, p. ex., Rosenzweig and Parry, 1994 ; Jones and Thornton, 2003 ; Parry et al., 2004). D'autres études se concentrent sur les conséquences de la variation du climat sur la valeur des terres (Mendelsohn et al., 1994 ; Schlenker et al., 2005) ou encore sur les profits agricoles (Deschênes and Greenstone, 2007), afin d'évaluer les conséquences éventuelles du changement climatique, au niveau mondial ou régional. Les études conduites à l'échelle mondiale indiquent que les pays développés économiquement ne seront pas impactés de la même manière que les pays en développement, plus vulnérables aux aléas climatiques (Rosenzweig and Parry, 1994 ; Fischer et al., 2005).

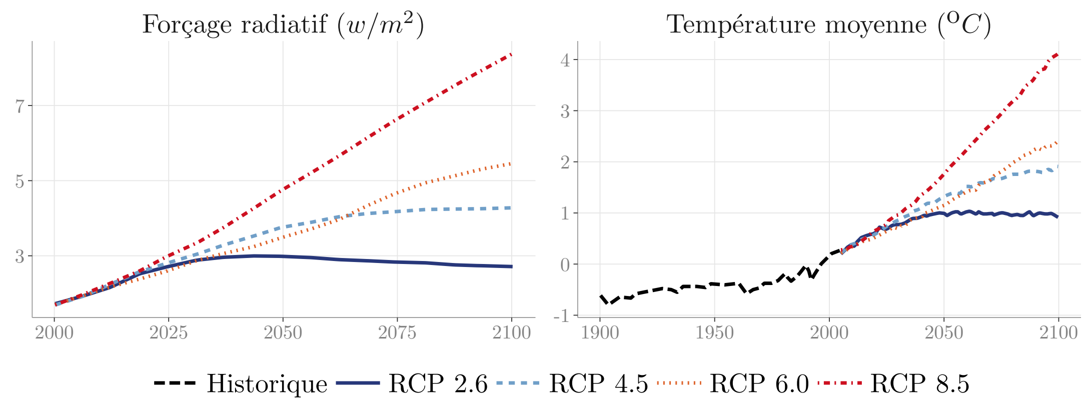
Cette thèse représente une tentative de contribuer au débat scientifique à l'égard du changement climatique et de ses effets sur l'agriculture. Elle s'appuie sur des méthodes empiriques et théorique au travers de quatre études, couvrant différentes échelles géographiques, tantôt concernant les pays en développement, tantôt concernant des pays développés.

Le reste de ce résumé propose de revenir sur les concepts clés de la thèse. La section 1 décrit brièvement ce qu'est le changement climatique et fournit des détails relatifs aux différents scénarios climatiques utilisés par les chercheurs afin d'estimer les effets potentiels du changement climatique sur la planète. La section 2 présente de manière plus détaillée les efforts fournis dans la littérature dans l'examen des effets du climat sur l'agriculture, et propose un bref aperçu des méthodes principales retenues par les chercheurs à cet effet. Enfin, la section 3 décrit la structure de la thèse, organisée en quatre chapitres.

Le climat change

Les preuves scientifiques sont très nombreuses : le climat global se réchauffe. Le Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC), un organe international des Nations Unies créé en 1988 afin d'évaluer sans parti pris la question du changement climatique, et regroupant des milliers de scientifiques définit le changement climatique comme : « *variation de l'état du climat, qu'on peut déceler (par exemple au moyen de tests statistiques) par des modifications de la moyenne et/ou de la variabilité de ses propriétés et qui persiste pendant une longue période, généralement pendant des décennies ou plus.* » (Edenhofer et al., 2014). Les résultats du dernier rapport de 2014 du GIEC prédisent une augmentation globale de la température moyenne de surface, en partie due à l'augmentation de la concentration anthropique (c'est-à-dire causée par les activités humaines) des gaz à effet de serre. Plus cette concentration est élevée, plus sera celle de la température moyenne de surface. Depuis la période pré-industrielle, c'est-à-dire, depuis environ la moitié du XVIIIe siècle, la concentration en gaz à effet de serre tels le dioxyde de carbone (CO_2), le méthane (CH_4) ou l'ozone (O_3) a augmenté de manière significative. En effet, la concentration en dioxyde de carbone dans l'atmosphère a augmenté de 43% depuis l'ère pré-industrielle pour atteindre 339.5 parties par million (ppm) en 2016. Dans le même temps, la concentration en méthane s'est intensifiée de 154% pour atteindre 1834 ppm en 2016, et celle de l'ozone troposphérique s'est accrue de 42% pour atteindre 337 ppm en 2016 (Blasing, 2009). Au cours des prochaines années, la concentration en gaz à effet de serre devrait continuer de grimper. Il existe cependant une forte incertitude concernant à la fois la valeur de cet accroissement d'ici la fin du XXI[e] siècle ainsi que le sentier conduisant à cette valeur. Ces concentrations dépendront, entre autres, de la croissance démographique, du développement social et du progrès technique. De nombreuses hypothèses doivent donc être émises, tout particulièrement à propos de l'activité humaine, afin d'estimer les niveaux potentiels de concentration en gaz à effet de serre dans un proche avenir. La projection de variables climatiques en dépend. Afin de fournir une base commune pour les chercheurs, il est courant de prendre appui sur des scénarios climatiques bien définis, développés par la communauté scientifique. Cela permet alors d'analyser le changement climatique et ses impacts.

Le GIEC, dans son dernier rapport (Edenhofer et al., 2014), a adopté quatre trajectoires différentes des émissions de gaz à effet de serre, appelées scénarios RCP (pour "*Representative Concentration Pathways*"), représentant différentes alternatives possible d'émissions en fonction des scénarios auparavant utilisés dans la littérature. Les noms de ces quatre scénarios reflètent la valeur du forçage radiatif à l'horizon auquel ils sont simulés, c'est-à-dire 2100 : les scénarios RCP 2.6, RCP 4.5, RCP 6.0 et RCP 8.5 sont ainsi caractérisés par un forçage radiatif en 2100 de $2,6W/m^2$, $4,5W/m^2$, $6,0W/m^2$, et $8,5W/m^2$ respectivement. Le forçage radiatif d'un gaz correspond à la différence entre le rayonnement solaire entrant et le rayonnement infrarouge sortant, et est influencé par la concentration de ce gaz. Plus la concentration est élevée, plus la balance des rayonnements entrants et sortants est élevée, ce qui entraîne une augmentation des températures de surface. Par conséquent, la température de surface globale sur Terre devrait être la plus basse pour le scénario RCP 2.6 et la plus élevée pour le RCP 8.5. Le sentier permettant d'atteindre les niveaux de forçage radiatif diffère parmi les scénarios, comme le montre le graphique de gauche de la fig. 3. Dans le premier scénario, le RCP 2.6, c'est-à-dire le moins pessimiste en termes de concentration de gaz à effet de serre, un pic de forçage radiatif est atteint vers 2030 et diminue lentement par la suite. Les deux scénarios suivants, le RCP 4.5 et le RCP 6.0 sont caractérisés par des niveaux de rayonnements plus élevés, avec une stabilisation respective sans dépassement à $4,5W/m^2$ et $6,0W/m^2$. Le dernier scénario, le RCP 8.5, est plus pessimiste et reflète des émissions de gaz à effet de serre qui augmentent continuellement, entraînant une valeur de forçage radiatif de $8,5W/m^2$ d'ici 2100. De plus amples détails peuvent être trouvés dans Van Vuuren et al. (2011).



Notes : Chaque courbe représente la tendance du forçage radiatif (gauche) et la variation correspondante du changement de température moyenne globale par rapport à 1986-2005 (droite) pour l'un des quatre scénarios RCP. Le graphique de gauche est une reproduction de la Figure 10 de Van Vuuren et al. (2011) ; celui de droite de la Figure 12.1 de Collins et al. (2013).

FIGURE 1 : Tendances du forçage radiatif et changement global de la température moyenne

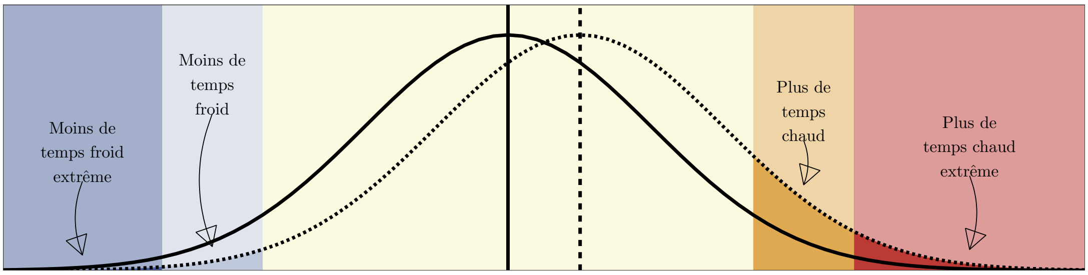
Les tendances du forçage radiatif de chaque scénario peuvent être utilisées dans des modèles climatiques, afin de simuler un climat potentiel jusqu'à 2100, à différentes échelles spatio-temporelles. La variation moyenne de la température moyenne globale pour les quatre scénarios est représentée sur le graphique de droite de la fig. 3. D'ici la fin du XXI[e] siècle, comparativement aux niveaux de 1986–2005, selon les résultats relayés par le GIEC (Collins et al., 2013), la variation de la température moyenne tablant sur le scénario 2.6 serait vraisemblablement comprise entre $0,3^oC$ et $1,7^oC$. Sous les scénarios RCP 4.5 et 6.0, la variation serait plus élevée, avec des valeurs allant de $1,1^oC$ à $2,6^oC$ et de $1,4^oC$ à $3,1^oC$, respectivement. Dans le pire des cas, sous le scénario RCP 8.5, il est probable que l'augmentation de la température moyenne globale soit comprise entre $2,6^oC$ et $4,8^oC$.

Ces valeurs de changements sont des moyennes à l'échelle mondiale. En réalité, une forte hétérogénéité dans les projections climatiques s'observe, avec un changement prévu sur les terres plus élevé que celui des océans. En outre, les changements sur les terres ne devraient pas être uniformes ; certaines régions devraient en effet connaître une augmentation de la température moyenne tandis que d'autres seraient soumises à des climats plus froids.

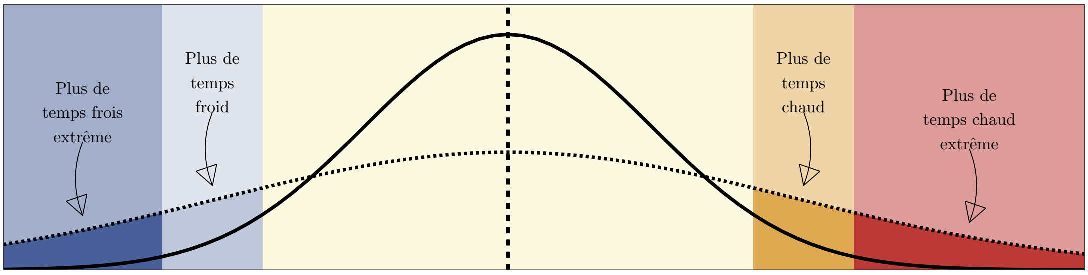
Une modification des statistiques climatiques a un impact direct sur ses réalisations. Une distinction entre ces deux notions doit être faite, comme l'ont souligné Schlenker et al. (2006). La principale différence entre les réalisations du climat ("*weather*") et le climat lui-même ("*climate*") est l'échelle temporelle. Les réalisations du climat correspondent aux conditions météorologiques à un moment distinct, alors que le climat se réfère à une moyenne des statistiques climatiques sur une longue période de temps. Par conséquent, si nous considérons les conditions météorologiques comme la réalisation de multiples variables aléatoires, la réalisation du climat peut être considérée comme un tirage à court terme de ces variables. Le climat peut quant à lui être considéré comme la moyenne de ces tirages sur le long terme. Une illustration simplifiée peut aider à mieux appréhender cette distinction, et ainsi donner une meilleure idée des effets sous-jacents d'une modification des statistiques du climat sur ses réalisations. Par commodité, nous pouvons supposer que la température de surface est le résultat d'un tirage aléatoire selon une distribution gaussienne, comme représentée par la fig. 4. Aussi, comme montré par la fig. 4(a), une augmentation de la moyenne de la température conduirait à une augmentation de la probabilité d'occurrence de valeurs chaudes ou extrêmement chaudes, accompagnée d'une diminution de la probabilité d'occurrence de valeurs froides ou très froides. Cependant, le GIEC, dans son dernier rapport, indique que les modifications opérées sur les systèmes climatiques comprennent également un changement dans la variabilité du climat. Reprenons alors notre exemple, en considérant à présent un changement uniquement dans la variance des températures, en conservant la moyenne à son niveau initial. La fig. 4(b) illustre ce cas. Si la variance croît, la distribution devient plus plate, impliquant *de facto* une augmentation de la probabilité d'occurrence des valeurs à la fois froides et chaudes. Une combinaison entre l'augmentation de la moyenne et de la variance, comme illustré par la fig. 4(c), se solde par une augmentation de l'occurrence de valeurs chaudes et extrêmement chaudes.

Cette illustration est une simplification de ce qui est en réalité attendu avec le changement climatique. De nombreux effets tels l'hétérogénéité spatiale et la saisonnalité devraient être pris en compte. De plus, la loi de probabilité régissant les températures n'est sûrement pas gaussienne. L'exemple simplifié permet toutefois de comprendre la base des mécanismes liés au changement climatique. Il devient plus facile d'imaginer comment le nombre et la gravité des événements extrêmes tels que les tornades, les fortes pluies ou les sécheresses devraient augmenter d'ici la fin du siècle.

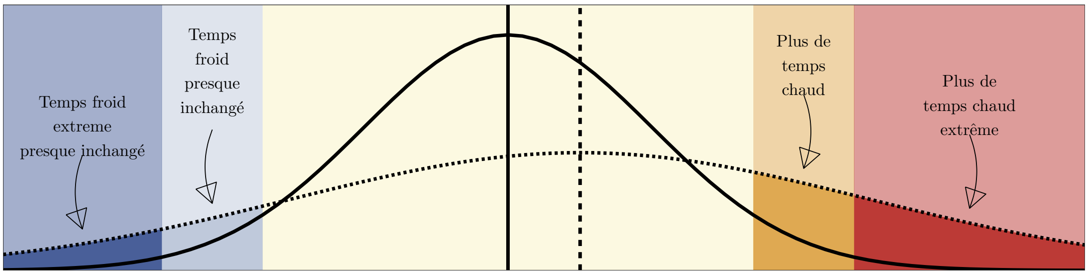
Cependant, beaucoup d'incertitude subsiste quant à l'ampleur de ces changements et de leurs effets sur notre société, notamment sur l'économie. En particulier, sur les systèmes agricoles qui sont au cœur des défis du changement climatique, en raison leur forte dépendance aux conditions météorologiques.



(a) Augmentation de la moyenne



(b) Augmentation de la variance



(c) Augmentation de la moyenne et de la variance

Notes : les lignes solides et pointillées représentent la distribution des températures avant et après une modification des moments d'ordre 1 et 2, respectivement (sous hypothèse de normalité). Cette figure est une reproduction de la Figure 1.8 issue de Cubasch et al. (2013).

FIGURE 2 : Effets du changement climatique sur la distribution des températures

MODÉLISATION DES CONSÉQUENCES DU CHANGEMENT CLIMATIQUE SUR L'AGRICULTURE

Les systèmes agricoles dépendent étroitement des variables climatiques telles que la température et les précipitations. Certaines régions ont des conditions naturelles plus adaptées aux activités agricoles que d'autres. Par exemple, les zones tempérées sont plus propices à la culture de céréales que les zones tropicales, les températures et les niveaux de précipitations observés dans ces premières étant plus propices aux besoins de certaines céréales telles que le blé ou le maïs. Le climat peut en fait être considéré comme un intrant direct dans la fonction de production. Toutefois, contrairement à d'autres intrants tels que la main-d'œuvre, les engrais, les systèmes d'irrigation plus ou moins sophistiqués, les machines ou les méthodes agricoles, la météo ne peut être contrôlée par les agriculteurs. Par conséquent, la production agricole est vulnérable aux aléas météorologiques. Cette dépendance des systèmes agricoles à la météo pose des défis importants dans le contexte du changement climatique. Comme mentionné précédemment, le changement climatique devrait entraîner une modification des conditions météorologiques, accompagnée d'une augmentation des événements extrêmes pouvant entraîner des pertes importantes de production. Le changement climatique est très susceptibles d'affecter la sécurité alimentaire au niveau mondial comme à l'échelle des pays, *via* un accès réduit à la nourriture. Cela soulève des inquiétudes concernant l'un des nombreux défis auxquels le secteur agricole doit faire face, à savoir sa capacité à produire suffisamment de nourriture pour couvrir les besoins de la population. En outre, le nombre de personnes vivant sur la planète devrait continuer à croître au cours des prochaines années, rajoutant davantage de difficulté à ce défi. En effet, la demande mondiale de récolte de 2005 à 2050 devrait augmenter de 100 à 110 % (Tilman et al., 2011). Par conséquent, il apparaît primordial d'étudier la relation entre l'agriculture et le climat, afin de pouvoir s'adapter aux nouvelles conditions météorologiques que nous réserve l'avenir.

Pour pouvoir relever ces défis, une grande partie de la littérature se concentre directement sur les fonctions de production agricole ou, en utilisant un cadre appelé « ricardien », examine les profits agricoles réalisés. Une autre partie de la littérature s'intéresse à la manière avec laquelle la réponse de l'agriculture aux variations climatiques affecte le reste de l'économie.

Les fonctions de production agricole

Le nombre de contributions scientifiques documentant la relation entre le climat et la fonction de production agricole a considérablement augmenté au cours des dernières décennies. Deux méthodes différentes se distinguent dans cette partie de la littérature. La première simule les rendements des cultures en utilisant des modèles agronomiques, tandis que la seconde repose sur des modèles statistiques pour examiner les liens observés entre les rendements et le climat.

Les modèles de simulation de cultures sont utilisés pour modéliser la croissance des cultures. Certains sont conçus pour une culture spécifique, comme CERES-Maize pour le maïs (Jones et al., 1986) ou CERES-Wheat pour le blé (Ritchie and Otter, 1985). D'autres peuvent être adaptables à un large éventail de cultures, telles que les modèles STICS qui peuvent modéliser le blé, le maïs, le soja, le sorgho et bien d'autres cultures de croissance (Brisson et al., 1998). Dans les deux cas, les phases de développement des cultures sont modélisées par des équations mathématiques dans un premier temps. Ces équations tiennent compte de nombreux facteurs telles que les conditions du sol, le climat et les méthodes de gestion (Mearns et al., 1997). Une fois que le modèle est établi, il doit être calibré. À cette fin, les cultures sont cultivées dans des champs ou des terrains expérimentaux, sous différentes conditions environnementales, y compris météorologiques. Des niveaux différents de concentration en dioxyde de carbone peuvent également être testés. Comme mentionné précédemment, la concentration de ces gaz à effet de serre dans l'atmosphère affecte le climat par le forçage radiatif, mais elle joue également un rôle dans le processus physiologique de la photosynthèse et de la transpiration (Field et al., 1995). Par conséquent, être en mesure de capturer les effets fertilisants du dioxyde de carbone représente un atout considérable des modèles de simulation des cultures. En effet, lorsque les modèles de simulations de cultures sont ensuite utilisés, une fois calibrés, pour réaliser du contre-factuel, il est possible de leur soumettre de nouvelles valeurs de concentration en gaz à effet de serre reflétant un scénario climatique possible. Il est alors possible d'observer la réponse potentielle des cultures selon différents scénarios climatiques. Les modèles de simulation des cultures deviennent alors un outil puissant pour étudier les avantages potentiels et/ou les préjudices provoqués par le changement climatique.

La réponse de la production agricole au changement climatique a été largement étudiée dans la littérature à l'échelle de régions plus ou moins vastes (voir, p. ex., Aggarwal and Mall, 2002 pour les rendements du riz en Inde ; Xiong et al., 2009 pour la production de maïs, de blé et de riz en Chine ; Jones and Thornton, 2003 pour les rendements de maïs en Afrique de l'Ouest) ou à l'échelle mondiale (voir, p. ex., ; Lobell and Field, 2007 pour le blé, le riz, le maïs et le soja ; Rosenzweig et al., 2014 pour le blé, le riz et le soja). Récemment, Bassu et al. (2014) ont montré que l'utilisation d'une combinaison de modèles plutôt qu'un seul permet de simuler les rendements agricoles avec une précision accrue ; ils ont également montré qu'une augmentation de la température diminue les rendements du maïs.

Cependant, les modèles de simulation des cultures présentent certains inconvénients.

Tout d'abord, ils sont calibrés dans des zones géographiques spécifiques et peuvent donc représenter avec précision les différentes étapes de croissance de cette région particulière. Ils peuvent dans le même temps ne pas être représentatifs de toutes les régions du monde. Une autre lacune majeure de ces modèles est qu'ils ne tiennent pas compte de la possibilité pour les agriculteurs de s'adapter à une nouvelle condition climatique. En effet, ces modèles, même s'ils sont adaptables à de multiples cultures, sont calibrés pour un type donné de culture, et ne modélisent donc pas la possibilité pour l'agriculteur d'en changer si les conditions climatiques ne sont plus adaptées. Par ailleurs, toutes les différences de résultats sont supposées être attribuables uniquement à des changements dans les variables affectant la croissance des cultures, telles que la température ou les précipitations. Cela conduit probablement les modèles de simulation à surestimer les effets du changement climatique (Adams et al., 1990 ; Parry et al., 2004). En outre, les conditions économiques telles que la variabilité des prix ne sont pas prises en compte par ces modèles, de sorte que les agriculteurs sont considérés comme myopes face à leur environnement économique et *de facto* incapables de se tourner vers une activité offrant de meilleures opportunités.

La question de la représentativité spécifique à la localisation peut être en partie traitée par des modèles statistiques. Dans ces cadres d'analyse, les variations des rendements des cultures sont modélisées en fonction des variations d'autres variables telles que les intrants utilisés, les conditions économiques auxquelles sont confrontés les agriculteurs, la qualité du sol, la météo ou les conditions climatiques. La méthode repose sur des observations historiques pour estimer la forme fonctionnelle reliant la variable d'intérêt à son prédicteur. Il est donc possible d'examiner les déterminants des rendements des cultures à des échelles spatiales plus importantes que celles utilisées dans les analyses de simulation de cultures, en s'appuyant sur les données observées à plusieurs endroits. Une fois que le modèle statistique est estimé, il est possible de lui soumettre de nouvelles conditions météorologiques et de prédire quelle sera la réponse de la variable d'intérêt. La valeur prédite peut *de facto* être comparée à la réalisation historique, et le changement peut alors être attribué à la variation des conditions climatiques.

Dans les modèles statistiques, la météo est considérée comme un apport spécial dans la production agricole puisqu'elle ne peut être contrôlée dans des configurations naturelles et est donc considérée comme une variable exogène. Ainsi, les conditions climatiques agissent comme une "expérience naturelle" (Angrist and Krueger, 2001, via Auffhammer et al., 2013). Le chercheur ne peut observer que l'issue de l'expérience sans pouvoir contrôler manuellement la quantité de l'intrant naturel. Cependant, les effets causaux de la météo sur les rendements des cultures peuvent être examinés et ont déjà conduit à de nombreuses études tentant de les quantifier. Il n'y a toutefois aucun consensus quant à l'ampleur des effets du changement climatique sur les rendements des cultures. Lobell et al. (2011) ont étudié la relation historique mondiale entre la température et quatre cultures : le maïs, le riz, le blé et le soja, de 1980 à 2008. Leurs résultats suggèrent un impact négatif de la température sur les rendements du maïs et du blé, réduisant les rendements de $3,8\%$ et de $5,5\%$, respectivement, avec la présence d'hétérogénéité régionale. Leurs résultats concernant les deux autres récoltes sont moins concluants, avec des baisses globales de $-0,1\%$ pour le riz et $-1,7\%$ pour le soja, avec des gains observés dans certaines régions annulant les pertes subies dans d'autres régions. You et al. (2009) ont trouvé des résultats similaires pour les rendements du blé en Chine, entre 1979 et 2000. Ils ont estimé une réduction des rendements du blé de 3% à 10% en raison d'une augmentation de la température de la saison de croissance moyenne d'un degré. Lobell and Asner (2003) ont estimé l'impact de l'augmentation des températures sur les rendements agricoles dans les comtés aux États-Unis, en utilisant des données de 1982 à 1998. Selon les résultats de l'article, chaque degré supplémentaire de la température moyenne entraîne une diminution de 17% des rendements du maïs et du soja. Dans la littérature, les simulations de changement de climat sont plus profondément évaluées en utilisant des scénarios climatiques. Par exemple, Schlenker and Roberts (2009) ont considéré différents scénarios pour les États-Unis et ont conclu que l'augmentation des températures d'ici la moitié du XXI^{e} siècle entraînerait une diminution substantielle des rendements du maïs, du coton et du soja par rapport aux rendements observés entre 1950 et 2005. Plus précisément, les pertes varieraient de -30% à -46% dans un scénario optimiste, et seraient encore plus désastreuses dans le pire des cas, allant de -63% à -82%. Schlenker and Lobell (2010) ont utilisé des données historiques en Afrique subsaharienne pour relier les rendements des cultures à la variation de la température, puis ont utilisé le modèle estimé pour évaluer les effets du changement climatique sur les rendements de maïs, de sorgho, de mil, d'arachide et de manioc. Pour l'ensemble des cultures, leurs résultats prévoient des rendements en déclin, allant de -8% à -22% d'ici la moitié du XXI^{e} siècle, comparativement aux rendements observés entre 1961 et 2000.

Toutes ces études considèrent les effets des covariables sur la moyenne de la variable de réponse. Certaines études (p. ex., Chen et al., 2004 ; Cabas et al., 2010) suggèrent d'utiliser la méthode de production de Just et Pope (Just and Pope, 1978), permettant *de facto* de caractériser les effets des variations climatiques à la fois sur les rendements des cultures mais également sur leur variabilité (McCarl et al., 2008).

L'avantage d'utiliser des modèles statistiques plutôt que des modèles de simulation de culture est que les premiers indiquent clairement les incertitudes du modèle en donnant des indicateurs statistiques concernant la qualité de l'estimation, ce qui n'est pas la norme avec les modèles de simulation de cultures (Lobell and Burke, 2010). Cependant, les modèles statistiques présentent certaines réserves. Même s'il est fréquent d'utiliser plusieurs variables météorologiques pour estimer les variations des rendements des cultures, cette pratique pourrait causer des problèmes de multicolinearité (Sheehy et al., 2006 ; Lobell and Ortiz-Monasterio, 2007), surtout lorsque les variables météorologiques sont désagrégées pour refléter les effets saisonniers. Une autre lacune des modèles statistiques est ce que Mendelsohn et al. (1994) appellent le « scénario des agriculteurs naïfs » ("*dumb farmer scenario*"). Dans ces modèles, l'accent est mis sur un seul type de culture, tout comme dans les modèles de simulation des cultures. Aussi, il est implicitement supposé que les agriculteurs ne peuvent pas s'adapter à un environnement variable offrant de nouvelles conditions climatiques. D'où l'expression employée par les auteurs. Par conséquent, l'analyse statistique des rendements des cultures pourrait ne pas être un bon outil pour prédire les variations à long terme.

L'approche ricardienne

Les modèles de simulation des cultures et leur homologue statistique ne tiennent pas compte de la capacité des agriculteurs à s'adapter à un nouvel environnement. Une manière de contourner cet écueil est fournie par Mendelsohn et al. (1994), qui suggèrent de regarder la valeur de la terre plutôt que les rendements. Dans leur travail pionnier, ils présentent une analyse intitulée « analyse ricardienne » du nom du célèbre économiste David Ricardo.

La méthodologie ricardienne est un modèle hédonique de tarification des terres agricoles qui met l'accent sur la valeur foncière. L'idée fondamentale est que le climat à long terme devrait être capitalisé en valeur foncière. Dans un marché concurrentiel, on suppose que le prix des terres agricoles reflète la valeur actualisée de tous les bénéfices futurs prévus qui en découlent. L'approche ricardienne mesure l'impact des variables climatiques sur la productivité de la terre ou la valeur des terres agricoles en exploitant les différences transversales dans l'utilisation des terres et les conditions météorologiques. Il est à noter que les variables climatiques (moyennes sur du long terme) sont utilisées dans l'analyse ricardienne plutôt que dans les variables météorologiques (réalisations du climat, à court terme). En effet, un choc météorologique défavorable comme une tempête ou une sécheresse peut entraîner des pertes sur les rendements des cultures, mais peut avoir des effets ambigus sur les bénéfices : d'une part, la production peut être réduite et, par conséquent, diminuer les bénéfices ; d'autre part, en présence d'une inélasticité de la demande de produits agricoles, le marché peut s'ajuster en augmentant les prix, augmentant *de facto* les profits agricoles. Mais à long terme, les bénéfices devraient être réduits par un changement climatique adverse (Schlenker et al., 2006). En outre, à court terme, les agriculteurs peuvent être vulnérables aux chocs météorologiques, mais à long terme, ils peuvent adopter de nouvelles stratégies agricoles et ajuster leurs décisions concernant les niveaux d'intrants en réponse au climat auquel ils sont confronté. Par conséquent, l'utilisation de variables climatiques plutôt que des variables météorologiques est plus adaptée au cadre ricardien.

Au cours des deux dernières décennies, le cadre ricardien original a été largement appliqué dans de nombreux pays à travers le monde. La plupart des recherches antérieures utilisent des données transversales pour estimer les valeurs de la ferme sur les variables météorologiques. Des examens approfondis des applications pour les régions d'Afrique, d'Asie, d'Amérique du Sud et d'Amérique peuvent être trouvés dans le travail de Mendelsohn and Dinar (2009).

Dans l'article pionnier de Mendelsohn et al. (1994), l'accent a été mis sur les agriculteurs américains, et les résultats mettent en exergue l'hétérogénéité régionale des effets du climat sur les valeurs foncières. Les scénarios climatiques testés produisent des résultats mitigés, soulignant la présence de gagnants et de perdants. Les pertes subies par les perdants devraient toutefois être relativement inférieures à celles projetées en utilisant une analyse basée sur les rendements des cultures. Des résultats mitigés sont également observés en Afrique. Par exemple, Kurukulasuriya and Mendelsohn (2008) ont montré, en utilisant des données au niveau de l'exploitation provenant de 11 pays africains recueillis entre 2003 et 2004, que les effets du changement climatique sur les revenus nets diffèrent entre les exploitations irriguées et les exploitations pluviales. Les revenus nets de ces premières devraient augmenter jusqu'à 51% dans le meilleur des cas, alors que les revenus nets de ces dernières devraient chuter de -43% dans le cas d'un scénario climatique chaud et sec. Des résultats similaires entre les exploitations irriguées et non irriguées ont été trouvés en Chine (Wang et al., 2009). En Europe, Van Passel et al. (2016) ont estimé les effets du changement climatique à l'aide d'un grand échantillon d'exploitations agricoles en Europe occidentale. Bien que l'étude souligne différents effets régionaux, elle montre également que les exploitations agricoles européennes sont plus sensibles au réchauffement projeté que les exploitations américaines.

Un certain nombre de critiques à l'égard de l'approche ricardienne a été émis. Une faiblesse majeure réside dans le fait que les compétences non observables des agriculteurs ne sont pas incorporées dans l'analyse. Cette lacune a conduit certains chercheurs à introduire des données temporelles pour tenir compte du problème des variables omises, en ajoutant des variables indicatrices des régions dans le modèle (voir, p. ex., Schlenker et al., 2006 ; Deschênes and Greenstone, 2007 ; Kim et al., 2009 ; Cabas et al., 2010). Contrairement aux modèles de simulation des cultures, le cadre ricardien ne tient pas compte des effets fertilisants du CO_2, ce qui donne des résultats biaisés. Une autre faiblesse du modèle ricardien réside dans le fait qu'il n'intègre pas les effets sur les prix. Dans l'approche ricardienne, la variation des valeurs foncières sur les zones climatiques est due à des changements dans les variables climatiques. Une forte hypothèse est que les prix des intrants et des produits restent inchangés. Une attention particulière devrait être accordée sur ce point, car les prix des cultures tendent à être plus volatiles de nos jours (Cline, 1996 ; Schlenker et al., 2005).

Enfin, le modèle suppose implicitement que les agriculteurs ne sont pas confrontés à des coûts d'ajustement. Par conséquent, les résultats fournis par les modèles ricardiens devraient être considérés comme une estimation de la limite inférieure des coûts du changement climatique (Quiggin and Horowitz, 1999).

Les impacts économiques du changement climatique

Au lieu de se concentrer uniquement sur la fonction de production agricole, un nombre important d'études évalue plutôt les impacts du changement climatique sur l'économie. Certaines tentatives sont faites à l'échelle mondiale ou dans des zones géographiques plus spécifiques.

Les études portant sur l'économie mondiale mettent en évidence l'existence de gagnants et de perdants sous de nouvelles conditions reflétant le changement climatique. Une méthodologie largement utilisée consiste à prédire la réponse des rendements des cultures sous des scénarios climatiques projetés. Ces scénarios sont communément donnés par un modèle de circulation générale (GCM), c'est-à-dire un modèle climatique. Ensuite, les rendements agricoles prévus sont incorporés dans un modèle d'équilibre général qui évalue la production agricole ainsi que les prix des cultures. Il est également possible de s'intéresser à des questions de sécurité alimentaire en estimant le nombre de personnes exposées à la famine en fonction de la taille de la population, de la production agricole et des prix agricoles. Rosenzweig and Parry (1994) ont fourni une contribution célèbre à cette littérature. Ils ont identifié une distinction entre les pays en développement et les pays développés, les premiers étant plus vulnérables au changement climatique que les derniers. Cette distinction est un résultat commun dans la littérature (voir p. ex., Parry et al., 2004 ; Fischer et al., 2005), en raison de la prédominance de l'agriculture dans les pays en développement (Tubiello and Fischer, 2007). Une autre explication à ce résultat est que les pays en développement sont placés de manière disproportionnée à des latitudes faibles ou proches des tropiques, où les conditions climatiques ne sont pas optimales pour les activités agricoles, en raison de la grande variabilité météorologique.

Une autre façon d'examiner les effets globaux du changement climatique sur l'économie est d'utiliser une autre approche d'équilibre général appelée « modèles d'évaluation intégrée » (IAM, pour "*Integrated Assessment Models*"). Les IAM sont des modèles mathématiques qui combinent dans un même cadre les connaissances sur le climat, l'économie, la démographie et les décisions politiques qui influent sur les émissions de gaz à effet de serre (voir p. ex., Nordhaus, 1991 ; Nordhaus, 1994 ; Nordhaus and Yang, 1996 ; Tol, 2002). Ces modèles évaluent le coût social du carbone en évaluant les changements dans le bien-être en raison des nouvelles conditions climatiques. Le mécanisme repose sur l'existence d'une fonction de dommage qui relie la température au PIB, de sorte qu'une augmentation de la température pourrait nuire à la production mondiale. Les IAM peuvent être utilisés comme outil d'analyse des politiques, en soumettant différents scénarios climatiques au modèle et en modélisant différentes politiques basées sur le coût social du carbone, c'est-à-dire l'estimation monétaire des dommages causés de manière directe ou non par l'émission d'une tonne de CO_2.

Les IAM, comme tout autre outil, présentent des lacunes. L'une d'elles concerne la fonction de dommages. Comme indiqué par Weitzman (2010), la fonction de dommage est « *un lien notoirement faible dans l'économie du changement climatique*[1] », car des hypothèses doivent être émises concernant sa forme fonctionnelle, et parce que ces hypothèses peuvent modifier considérablement les conclusions apportées par les IAM. Pindyck (2013) a également noté que les IAM ne tiennent pas compte de l'occurrence d'événements météorologiques catastrophiques, qui peuvent avoir des répercussions économiques très importants.

Beaucoup d'études se concentrent sur des zones géographiques plus spécifiques. La distinction entre économie en développement et économie développée est de nouveau

[1] La citation dans le papier est la suivante : « a notoriously weak link in the economics of climate change ».

présente dans ces études, puisque les défis auxquels sont confrontés les pays en développement sont quelque peu différents de ceux auxquels sont confrontés les pays développés.

Dans les pays en développement, le secteur agricole représente généralement une part importante du PIB national. Ces pays dépendent donc fortement de leur secteur agricole, de sorte que des conditions météorologiques défavorables peuvent avoir des répercussions importantes au niveau national. Un choc météorologique néfaste affectant la production agricole peut créer une situation de pénurie alimentaire entraînant une augmentation des prix. En 2016, les pays d'Afrique australe ont été touchés par une deuxième saison consécutive de sécheresse entraînant de mauvaises récoltes. Selon la FAO, les conséquences sont dramatiques, exposant près de 40 millions de personnes à l'insécurité alimentaire. La même année, de nombreux états indiens souffraient également de fortes sécheresses couplées à une faible mousson. Ces conditions météorologiques désastreuses ont créé un déficit en eau affectant la production agricole et entraînant une augmentation des prix. La situation économique de millions de personnes s'en est vue menacée en Inde, pays dans lequel environ la moitié de la population travaille dans le secteur agricole.

Le changement climatique devrait être accompagné par une augmentation du nombre d'événements extrêmes. Si le changement n'est pas trop important, l'être humain pourra s'adapter aux nouvelles conditions. Un grand nombre d'études se penche sur la question de l'adaptation, notamment celle des agriculteurs, pour déterminer des pratiques permettant d'atténuer les effets globalement néfastes du changement climatique sur la production alimentaire. Par exemple, Butt et al. (2005) ont montré que l'adoption de nouvelles techniques agricoles, de cultures mixtes ou l'utilisation de variétés de cultures plus résistantes à la chaleur peuvent aider les agriculteurs du Mali à mieux faire face au changement climatique et à atténuer les dommages généraux causés par ce changement. Di Falco et al. (2011) ont constaté que les ménages agricoles qui se sont adaptés à un climat changeant ont tendance à produire plus que les ménages agricoles qui ne se sont pas adaptés et que l'accès au crédit ainsi que la détention d'information relative au climat sont des déterminants importants de l'adaptation. Si les coûts de l'adaptation sont trop élevés, les personnes confrontées à des conditions météorologiques trop hostiles pourraient être forcées d'émigrer, comme le montrent Black et al. (2011).

Dans les pays à haut revenu, dans lesquels le secteur agricole n'est pas aussi important en termes de PIB, les défis sont quelque peu différents mais méritent toutefois d'être soigneusement étudiés. Des pays comme les États-Unis d'Amérique, l'Australie ou les membres de l'Union européenne sont des acteurs clés du marché agricole. Selon la FAO, au cours des trois dernières années, environ 40% de la production mondiale de céréales provenaient de pays développés (FAO, 2017), principalement d'Amérique du Nord et d'Europe. Les pays développés sont souvent les producteurs principaux sur les marchés agricoles. Par conséquent, des accidents météorologiques peuvent fortement affecter la production mondiale et générer des problèmes de sécurité alimentaire. En 2003, la température moyenne d'été en Europe était jusqu'à 6°C au-dessus de sa moyenne moyenne de 1998-2002 et les précipitations étaient 50% inférieures à la moyenne (Ciais et al., 2005). Les pays d'Europe occidentale ont été gravement touchés par la vague de chaleur de l'été, avec une augmentation de la mortalité et des incendies de forêt. Le secteur agricole a également souffert de la vague de chaleur : par rapport à l'année précédente, la production des cultures a diminué de 36% et de 30% en Italie et en France, respectivement ; le déficit fourrager était du même ordre (Easterling et al., 2007) ; 4 millions de volailles sont morts et la production de lait a été réduite (García-Herrera et al., 2010). Quelques années plus tard, en 2012, les États-Unis ont également subi un choc météorologique extrêmement négatif qui a affecté sa production de maïs. Selon le ministère de l'Agriculture des États-Unis, la production agricole a diminué de 13% par rapport à l'année précédente. Comme les États-Unis sont parmi les plus grands exportateurs mondiaux du maïs, et puisque les réserves mondiales de maïs étaient faibles à ce moment-là, la baisse de la production a eu une incidence sur les prix mondiaux de cette céréale, qui ont augmenté de 25% pour atteindre un sommet encore supérieur à celui enregistré au cours de la crise des prix alimentaires de 2007 à 2008 (Chung et al., 2014). En somme, lorsque des acteurs importants des marchés agricoles sont touchés par un événement climatique affectant la production, le marché s'adapte à la situation de carence par une augmentation du prix, pouvant conduire à une situation de crise alimentaire.

Par conséquent, les conditions météorologiques affectent les pays en développement et les pays développés de manière différente.

Plan de la thèse

Cette thèse vise à contribuer au débat théorique et empirique sur le changement climatique et l'agriculture. Elle est structurée en deux parties contenant quatre essais complémentaires utilisant une variété de méthodes économétriques et théoriques répondant à la fois aux besoins des questions soulevées dans chaque étude et au type de données disponibles.

La première partie de la thèse consiste en deux analyses microéconomiques pour un pays en développement, l'Inde, se concentrant d'abord sur le côté de l'offre, puis se tournant vers le côté de la demande de la production agricole. La deuxième partie concerne les pays développés. Elle commence par une étude régionale impliquant plusieurs pays d'Europe occidentale, c'est-à-dire des pays ayant un impact significatif sur le marché mondial de l'agriculture. La dernière étape met en évidence l'intérêt de considérer une approche d'équilibre général pour examiner les interactions qui se déroulent entre le secteur agricole et le reste de l'économie, dans le contexte d'une petite économie ouverte.

Le chapitre 1, intitulé "***Climate Change and Profits : a Ricardian Analysis***" (« Une analyse ricardienne »), examine les décisions individuelles des agriculteurs d'un pays en développement dans lequel le secteur agricole représente une part non négligeable de l'économie nationale. L'objectif est de comprendre les effets de la variabilité météorologique sur les profits agricoles indiens et d'examiner les effets potentiels du changement climatique sur ces profits, sous différents scénarios climatiques. L'analyse conduite dans le premier chapitre adopte l'approche ricardienne qui lie les revenus nets par acre en fonction du climat, de la ferme et des caractéristiques des ménages. La fonction des revenus nets par acre est estimée à l'aide de données détaillées en coupe transversale. Bien que la plupart des études sur l'agriculture indienne soient menées sur des données à l'échelle du district, cette étude se déroule au niveau de l'exploitation individuelle. La répartition spatiale des observations permet une couverture raisonnable de l'ensemble du pays, fournissant des résultats généralisables à l'échelle indienne. Les mécanismes expliquant les variations des revenus nets par acre sont examinés à l'aide d'une régression quantile, ce qui permet une meilleure compréhension des impacts des variations climatiques sur la répartition des revenus nets par acre.

Les résultats empiriques montrent que les exploitations ayant des revenus nets par acre plus élevés semblent être plus affectées par les variables météorologiques en magnitude. Les exploitations dont les revenus nets par acre sont inférieurs ont tendance à bénéficier davantage de la pratique de diversification des cultures que des exploitations à fort revenu par acre. Dans une deuxième étape, deux scénarios climatiques différents selon les hypothèses sur les variations de la température moyenne et des précipitations totales sont envisagés. Les exploitations agricoles ayant un faible revenu net par acre connaissent des pertes moins importantes en grandeur mais plus importantes en pourcentage que les exploitations avec des revenus nets élevés par acre. À l'échelle du district, les résultats montrent plus d'hétérogénéité. Dans les deux scénarios, les districts du nord de l'Inde ont tendance à connaître une diminution des revenus nets par acre alors qu'un effet opposé est trouvé pour les districts du sud du pays.

Le chapitre 2, intitulé "***Climate Change and Food Security : a Farm-Household Model***" (« Changement climatique et sécurité alimentaire : un modèle de ménage »), utilise les résultats du premier chapitre comme point de départ : des effets hétérogènes du climat sur les profits agricoles ont été mis en exergue, en fonction du type de ménage. Dans le deuxième chapitre, les effets des variations climatiques sur les dépenses de production et de consommation agricoles sont étudiés pour différents types de ménages agricoles, en fonction de leur participation au marché du travail. Dans un premier temps, l'étude évalue les effets des variations climatiques sur la production agricole des ménages agricoles indiens. Ensuite, les résultats de la première étape sont utilisés pour estimer un système de demande quasi idéal ("*Almost Ideal Demand System*" pour différents types de ménages agricoles classés en fonction de leur régime de travail. Différents scénarios sur les prix ainsi que sur les variables climatiques sont ensuite testés pour évaluer les effets sous-jacents sur les consommations de décision. Comme dans le premier chapitre, l'étude utilise des données au niveau de l'exploitation agricole individuelle avec une couverture spatiale de l'Inde raisonnable. En outre, l'analyse complète la vue donnée dans le chapitre 1 en explorant à la fois l'offre et le côté de la demande des ménages agricoles.

La production agricole est sensible à la fois aux températures et aux précipitations. Les décisions de consommation sont également affectées par les conditions climatiques. En particulier, une augmentation de la pluviométrie totale entraîne une demande accrue de biens purement marchands et de produits d'origine animale ainsi qu'une diminution de la demande de céréales et de loisirs. En outre, la demande de céréales est plus affectée par la variation des précipitations pour les ménages autarciques par rapport aux autres types de ménages ruraux. En revanche, la demande pour les produits agricoles des ménages autarciques est moins affectée par la variabilité des températures. Les scénarios dans lesquels les précipitations et les températures sont modifiées présentent l'existence d'un arbitrage entre la demande de céréales et les produits d'origine animale.

Le chapitre 3, intitulé entitled “***Climate Change and Agricultural Yields : an European Case Study***” (« Rendements agricoles : étude du cas européen »), considère une vue plus agrégée pour des pays développés économique, ceux d’Europe occidentale. Une dimension temporelle est introduite en contraste avec les deux analyses précédentes. Cette caractéristique supplémentaire permet d’introduire la question de la volatilité des prix, qui s’est avérée fondamentale sur les marchés agricoles ces dernières années, bien que fréquemment ignorée dans la littérature. La volatilité des prix est en fait une question clé pour les pays européens, en particulier dans le contexte de l’abandon du soutien des prix pour les agriculteurs dans la Politique Agricole Commune (PAC). Le troisième chapitre intègre cette volatilité des prix de production dans une tentative d’étudier la relation entre les variations climatiques et les rendements de deux grandes cultures céréalières, à savoir le blé et le maïs. Les effets du changement climatique sur l’agriculture européenne dans différents scénarios alternatifs sont étudiés de manière empirique.

Les résultats empiriques présentent les effets des variables météorologiques saisonnières sur les rendements moyens ainsi que sur leur variabilité, pour le blé et le maïs. Les prix ont un impact positif et significatif sur les rendements du blé pour le nord de l’Europe, seulement après la réforme de la PAC. Avant cette réforme, l’effet des prix sur les rendements n’est pas statistiquement différent de zéro. Les modèles empiriques sont ensuite utilisés pour évaluer l’effet du changement climatique sur les rendements. Quatre scénarios de projection du climat reflétant les trajectoires de concentration des gaz à effet de serre sont testés. Des effets spatio-temporels mitigés sont trouvés. Les rendements du blé augmenteraient à l’échelle européenne dans la plupart des scénarios, mais les gains diminueront avec le temps pour les régions du nord, à long terme. Les résultats sont moins optimistes pour les rendements du maïs. À court terme, certaines régions du Nord connaîtraient des gains de rendement, mais ces gains se transformeraient en pertes sur le long terme. Ces pertes seraient même plus élevées dans le sud de l’Europe.

Le chapitre 4, intitulé “***Climate Change and Business Cycles***” (« Changement climatique et cycles économiques »), fournit une approche en équilibre général, contrairement aux trois premiers chapitres basés sur un cadre d’équilibre partiel. L’objectif de ce dernier chapitre est d’étudier l’influence des chocs météorologiques sur les cycles économiques, grâce à un modèle dynamique estimé pour une petite économie ouverte. Un modèle d’équilibre général intertemporel stochastique (MEGIS) original avec un secteur agricole dépendant de la météo est développé et estimé en utilisant des méthodes bayésiennes et des données trimestrielles pour la Nouvelle-Zélande au cours de la période d'échantillonnage allant de 1989 à 2014.

Les résultats du modèle suggèrent que les chocs météorologiques jouent un rôle important en expliquant les fluctuations macroéconomiques au cours de la période d'échantillonnage. Un choc météorologique mesuré par un indice de sécheresse agit comme un choc d'offre négatif caractérisé par une baisse de la production et une hausse des prix. Par ailleurs, les résultats montrent que les agriculteurs ne prévoient pas les chocs météorologiques et sont plutôt surpris par la variabilité des conditions climatiques. Enfin, l'augmentation de la variance des chocs météorologiques reflétant les changements climatiques potentiels entraîne une augmentation considérable de la volatilité des principales variables macroéconomiques, telles que la production et l'inflation.

General Introduction

By the end of 2015, nations around the world gathered in Paris for the twenty-first yearly session of the United Nations Conference of the Parties on Climate Change. The goal of that conference was to achieve a legally binding and universal agreement on climate, with the aim of mitigating global warming. This warming is believed, on the basis of the unequivocal scientific evidence, to primarily be caused by the increase in the concentration of greenhouse gas emissions resulting from human activities. While climate change may have positive effects on some regions, a vast number of scientific studies suggests that overall, it poses threats on the future of our planet. Consequently, the expectations were high for the United Nations Climate Change Conference in Paris. World leaders recognized the need to take action. To avoid the most catastrophic effects of climate change, signatory governments have agreed to sign a deal to keep the global temperature rise well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit it to 1.5 degree Celsius. This agreement entered into force less than a year later, in November 2016, and was ratified by 142 parties out of 195.

Implicitly, relying on a vast body of scientific literature, the signatories recognized that the 2 degrees limit represents a threshold below which adaptation seems still reasonable. However, the way of achieving these goals as well as the underlying costs of adaptation are still surrounded by lots of uncertainties. In fact, the financial cost of climate change is an economic issue that gave rise to a significant number of studies. Not only the literature attempts to assess the costs and benefits of mitigation, but it also tries to evaluate the cost of doing nothing (OECD, 2015). A review of this literature can be found in Dell et al. (2014).

A popular approach, introduced by Nordhaus (1994), consists in using dynamic mathematical models to represent the world. The basic idea is to consider a damage function linking temperature to GDP, the former being dependent on the level of greenhouse gas emissions. These models can be used to evaluate the potential economic benefits of policies (see, *e.g.*, Hope et al., 1993; Tol, 2005). There is however no consensus reached on what needs to be done, as some authors recommended urgent action (*e.g.*, Stern, 2007) while others suggested a more progressive approach with more action in the future and less control in the short run (*e.g.*, Nordhaus, 2007).

This global approach of measuring the impacts of climate change is complemented in the literature by partial approaches focussing on specific economic sectors. One of the particularly vulnerable sector is agriculture, which strongly depends on climate. Surprisingly enough, it is not explicitly mentioned in the decisions adopted by the Conference of the Parties in Paris. Yet, the potential impacts of climate change on agriculture, in spite of the relatively limited economic size of that sector, may pose substantial threats (OECD, 2015), especially regarding food security and hunger. A vast number of studies is thus devoted to the documentation of the relationship between agriculture and climate. A brand of the literature simulates crop growth using mathematical models (see, *e.g.*, Ritchie and Otter, 1985; Jones et al., 1986; Brisson et al., 1998). Coupled with climate models that simulate projection of the weather, crop growth models can be used to assess the effects of climate change on food sustainability (see, *e.g.*, Rosenzweig and Parry, 1994; Jones and Thornton, 2003; Parry et al., 2004). Another part of the literature focuses on the effects of varying climate on land value (see, *e.g.*, Mendelsohn et al., 1994; Schlenker et al., 2005) or on agricultural profits (see, *e.g.*, Deschênes and Greenstone, 2007), in an attempt to assess the potential consequences of climate change either at the global level, or at the regional level. Studies conducted at the global scale provide evidence that developed and developing countries will not be impacted by climate change the same way (Rosenzweig and Parry, 1994; Fischer et al., 2005), the latter being more vulnerable to climate variations.

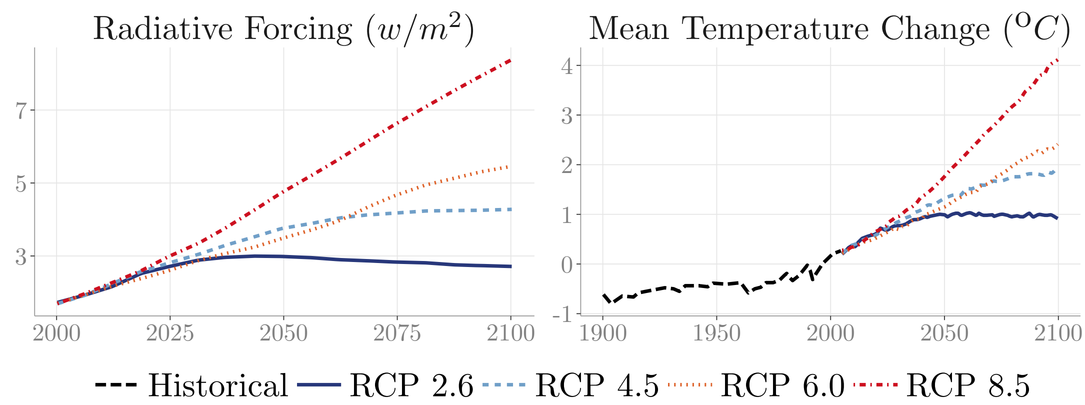
This thesis consequently aims to contribute to the scientific effort of investigating the potential impacts of climate change on agriculture. It relies on both theoretical and empirical methods to provide four analysis covering different geographical areas concerning either developing or developed countries.

The remainder of this introduction draws up the key concepts of this thesis. Section 1 briefly describes what climate change is and gives details on the different climate scenarios used by researchers to estimate the potential effects of climate change on our planet. Section 2 presents in more details the attempts of the literature to examine the effects of the weather and climate on agriculture and briefly reviews the main methods employed by scholars to address the effects of climate change on the agricultural sector. Finally, section 3 describes the structure of the thesis, organized in 4 chapters.

1 Climate is Changing

The scientific evidence is now overwhelming: global climate is warming. The International Panel on Climate Change, an international body set up in 1988 for assessing the science related to climate change and regrouping thousands of scientists defines climate change as "*a change in the sate of the climate that can be identified (*e.g.*, by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*" (Edenhofer et al., 2014). The results from the last 2014 report from the IPCC predict a likely global increase in the mean surface temperature partly due to increasing anthropogenic (*i.e.*, caused by human activity) concentration in greenhouse gases. The higher the concentration, the higher the increase in global mean surface temperature. Since the pre-industrial era, *i.e.*, since around 1750, the concentration of greenhouse gases such as carbon dioxide (CO_2), methane (CH_4) or ozone (O_3) has significantly increased. The concentration of carbon dioxide in the atmosphere has in fact increased by 43% since the pre-industrial era to reach 399.5 parts per million (ppm) in 2016. In the meantime, methane concentration has increased by 154% to reach 1834 ppm in 2016, and tropospheric ozone increased by 42% to reach 337 ppm in 2016 (Blasing, 2009). In the forthcoming years, greenhouse gas concentration is forecasted to rise even more. There is, however, a great uncertainty regarding both the concentration value by the end of the 21st century and the pathway leading to this value. These concentrations will depend, among other things, on demographic growth, on social development, and on technological change. Lots of assumptions thus need to be made, particularly on human activity, to assess the possible levels of greenhouse gas concentration in the near future. The projected outcome of climate variables depends on these assumptions. In order to provide a common ground to researchers, it is common practice to rely on well defined scenarios, developed by the research community. This then makes possible the analysis of possible climate change and its impacts.

The IPCC, in its last report (Edenhofer et al., 2014), adopted four different trajectories of greenhouse gas emissions, called Representative Concentration Pathways (RCPs), representing possible outcomes based on the scenarios used in the literature. Their names reflect the value of radiative forcing at the horizon at which they are simulated, *i.e.*, 2100 : the RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, are characterized by a level of radiative forcing in 2100 of $2.6W/m^2$, $4.5W/m^2$, $6.0W/m^2$, and $8.5W/m^2$, respectively. The radiative forcing of a gas corresponds to the difference between incoming solar radiation and outgoing infra-red radiation, and is influenced by the concentration of that gas. The higher the concentration, the higher the balance of incoming and outgoing radiations, resulting in higher surface temperatures. Hence, global surface temperature on Earth is expected to be the lowest for the RCP 2.6 scenario, and the highest for the RCP 8.5 one. The path to reach the levels of radiative forcing differs among the scenarios, as shown in the left panel of fig. 3. In the first scenario, the RCP 2.6, *i.e.*, the less pessimistic in terms of greenhouse gas concentration, a peak in radiative forcing is reached around 2030 and then slowly declines. The two next scenarios, the RCP 4.5 and RCP 6.0 are characterized by higher levels of radiations, with a stabilization without overshoot pathway to $4.5W/m^2$ and $6.0W/m^2$, respectively. The last scenario, the RCP 8.5, is more pessimistic and reflects continuously growing greenhouse gas emissions leading to a radiative forcing value of $8.5W/m^2$ by 2100. It is considered as a high emission scenario. More details can be found in Van Vuuren et al. (2011).



Notes: Each curve represents the trend in radiative forcing (left panel) and the corresponding change in global mean temperature change relative to 1986–2005 (right panel) for one of the four Representative Concentration Pathways. The graph on the left is a reproduction of Figure 10 from Van Vuuren et al. (2011), the graph on the right is a reproduction of Figure 12.1 from Collins et al. (2013).

FIGURE 3: Trends in Radiative Forcing and Global Mean Temperature Change

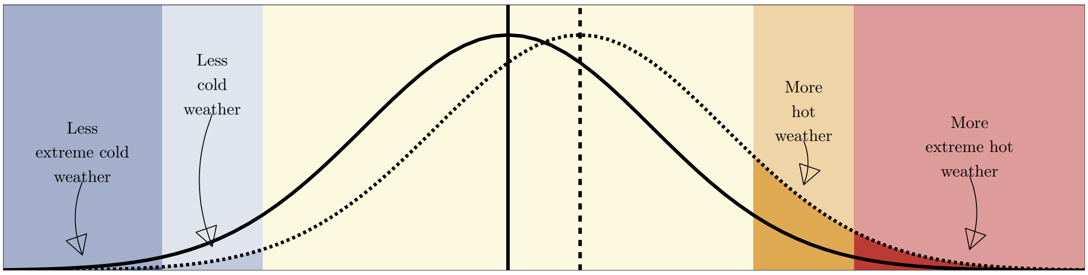
The trends in radiative forcing of each scenario are fed into climate models, to simulate potential climate up to 2100, at various spatio-temporal scales. The average change in global mean temperature for the four scenarios is reported in the right panel of fig. 3. By the end of the 21st century, relative to 1986–2005 levels, according to the IPCC results (Collins et al., 2013), the average temperature change based on the RCP 2.6 scenario is likely to be comprised between $0.3°C$ and $1.7°C$. Under the RCP 4.5 and

6.0, the change is higher, with values comprised between $1.1°C$ to $2.6°C$ and $1.4°C$ to $3.1°C$, respectively. Under the worst-case scenario, *i.e.*, the RCP 8.5, the likely global average change in mean temperature is comprised between $2.6°C$ to $4.8°C$.

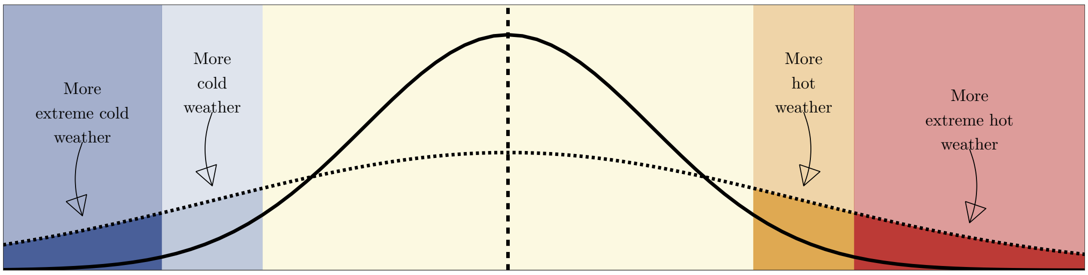
These values of changes are averages at the global scale. As a matter of fact, there is a lot of heterogeneity in the projections of climate, with an expected change over land higher than that of the oceans. In addition, the changes over land should not be uniform; some regions should experience higher temperatures while other should be subject to colder climates.

A modification in climate statistics has a direct impact on the weather. A distinction between these two notions needs to be made, as pointed out by Schlenker et al. (2006). The main difference between weather and climate is time scale, as the weather refers to meteorological conditions at a distinct moment in time, whereas climate refers to an average of climate statistics over an extended period of time. Hence, if we consider meteorological conditions as the realization of multiple random variables, the weather can be viewed as the short-run draws from these variables while climate can be viewed as the average of these draws in the long-run. A simplified example can be considered to get a better idea of the underlying effects of a modification in climate statistics on the weather. For convenience, we can suppose that observed surface temperatures are drawn from a Normal distribution, as depicted in fig. 4. Then, as shown in fig. 4(a), an increase of the surface temperature would lead to an increase in the probability of occurrence of hot weather and extreme hot weather, accompanied by a decrease in cold and extreme cold weather. However, in its last report, the IPCC predicts an increase in the variability of the weather as well. Let us consider first the effect of an increase in the variance of temperatures alone, keeping the mean value as its historical average. Figure 4(b) illustrates such a case. If the variance increases, the distribution becomes more flat, thus increasing the probability of occurrence of both cold and hot weather, as well as extreme temperatures. Figure 4(c) illustrates the case in which both mean and variance shift upwards. In this situation, more hot weather and much more extreme hot weather would occur.

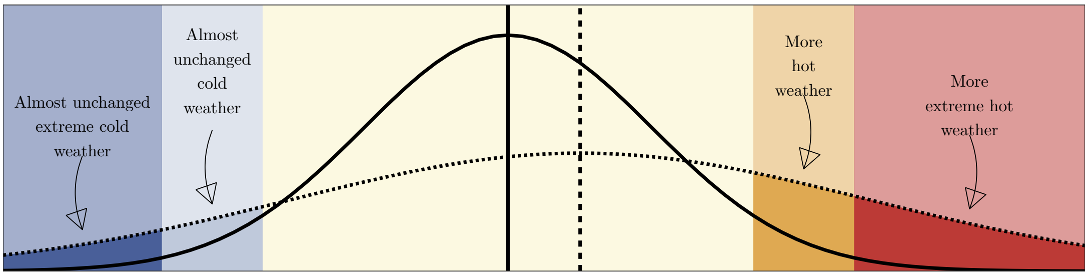
This illustration is a simplification of what is in reality expected with climate change, as one should also consider spatial heterogeneity as well as seasonal effects. Yet it enhances understanding of the basics of the possible effects of climate change. It becomes easier to imagine how the number and the severity of extreme events such as tornadoes, heavy rainfall or droughts should rise by the end of the century.



(a) Increase in Mean



(b) Increase in Variance



(c) Increase in Both Mean and Variance

Notes: The solid and dotted lines represent the previous climate distribution and the new climate distribution, respectively. This figure is a reproduction of Figure 1.8 from Cubasch et al. (2013).

Figure 4: Effects of Climate Change on the Distribution of Temperatures

However, a lot of uncertainty remains about the magnitude of these changes and their effects on our society, especially the economic ones. Agricultural systems lie at the very heart of the challenges of climate change, due to the particular dependency of agriculture on the weather conditions.

2 Modelling the Consequences of the Weather and Climate Change on Agriculture

Agricultural systems tightly depend on climatic variables such as temperature and precipitation. Some countries have natural conditions more suitable for agricultural activities than others. For example, crops farming is easier in temperate areas than in tropical zones, because the temperatures and the precipitation levels experienced in the former area fit more the needs of certain cereals such as wheat or corn. The weather can in fact be viewed as a direct input in the production function. However, contrary to other inputs such as labour, fertilizers, more or less sophisticated irrigation systems, machinery, or farming methods, the weather cannot be controlled by farmers. Hence, agricultural production may be vulnerable to poor weather conditions. This dependence of agricultural systems on the weather poses significant challenges in the context of climate change. As previously mentioned, climate change is expected to lead to a modification in the weather patterns, accompanied by an increase is extreme events that may cause substantial losses in production. Climate change is very likely to affect food security at the global level as well as at the country level, *via* a lower access to food. This raises concerns about one of the many challenges the agricultural sector must face, that is its capacity to produce enough food to feed the population. Besides, the number of people living on the planet is expected to keep growing in the forthcoming years, making this challenge even harder. The global crop demand from 2005 to 2050 is expected to increase by 100-110% (Tilman et al., 2011). Hence, it is of primary importance to study the relationship between agriculture and the weather, to be able to adapt to new weather conditions in the near future.

To be able to tackle these challenges, a large part of the literature focuses directly on the agricultural production functions or, using a framework named Ricardian, looks into the agricultural profits made by farmers. Another part of the literature looks at a different scale and considers how the responses of the agricultural system to climate modifications affect the rest of the economy.

2.1 The Agricultural Production Function

The number of scientific contributions documenting the relationship between the weather and agricultural production function has considerably grown in the last decades. Two different methodologies stand out in that part of literature. The first one simulates crop yields using agronomic models, while the second method relies on statistical models to examine the observed links between yields and the weather.

Crop simulation models are used to model crop growth. Some are designed for a specific crop, such as CERES-Maize for corn (Jones et al., 1986) or CERES-Wheat for wheat (Ritchie and Otter, 1985). Others can be adaptable to a wide range of crops, such as STICS models that can model wheat, corn, soybean, sorghum and many other crop growth (Brisson et al., 1998). In both cases, the development stages of crops are modelled through mathematical equations in a first step. These equations account for multiple factors such as soil conditions, the weather and management practices (Mearns et al., 1997). Once the model is established, it needs to be calibrated. To that end, crops are grown in fields or laboratory settings, subject to different environmental conditions, including varying weather conditions and varying levels of carbon dioxide. As previously mentioned, the concentration of greenhouse gas in the atmosphere affects climate through radiative forcing, but it also plays a role in the physiological process of photosynthesis and transpiration (Field et al., 1995). Hence, being able to capture the fertilizing effects of carbon dioxide represents a strength of crop simulation models, when they are fed with new data to simulate how crop growth is affected by new conditions. If these new conditions reflect a varying climate in accordance with a projected scenario, crop simulation models become a powerful tool to study the potential benefits and harms brought on by climate change.

The response of crop production to climate change has been extensively studied in the literature at the regional scale (see, *e.g.*, Aggarwal and Mall, 2002 for rice yields in India; Xiong et al., 2009 for corn, wheat, and rice yields in China; Jones and Thornton, 2003 for maize yields in west Africa) ; or at the global scale (see, *e.g.*, Lobell and Field, 2007 for wheat, rice, maize, and soybean; Rosenzweig et al., 2014 at for corn, wheat, rice and soybean). Recently, Bassu et al. (2014) have shown that using an ensemble of multiple models enables to simulate with better accuracy absolute yields than using a single model, and that increasing temperature strongly diminished corn yields.

Crop simulation models however present some drawbacks. First, they are calibrated in specific locations, and therefore may represent very well the different growth stages for that particular region, but might not be representative of all the regions of the world. Another major shortcoming of these models is that they fail to account for the possibility of farmers to adapt to a new climate condition. These models, even if adaptable to multiple crops, are calibrated for a given type of crops, and therefore do not model the possibility of the farmer to switch crops if the climate conditions are no longer suitable for that crop. In addition, all differences in outcomes are assumed to be due to changes in the variables affecting crop growth, such as temperature or precipitation. This pitfall probably leads crop simulation models to overestimate the effects of climate change (Adams et al., 1990; Parry et al., 2004). Besides, economic conditions such as price variability are not taken into account by these models, so that farmers are considered blind to their economic environment and therefore unable to switch to an activity offering a better opportunity.

The issue of location-specific representativity can be tackled by statistical models. For these frameworks, the variations of crop yields are modelled as the response to the variations of other variables such as inputs used, economic conditions faced by farmers, quality of soil, the weather or climate conditions, and so on. The method consists in relying on historical observations to estimate the functional form linking the variable of interest to its predictor. It is thus possible to examine the determinants of crop yields at larger spatial scales than those used in crop simulation analyses, relying on data observed at multiple locations. Once the statistical model is estimated, it is possible to assess new weather or climate conditions and predict the outcome of the variable of interest in such conditions. The predicted value can *de facto* be compared to the historical realization, and the change can be attributed to the varying conditions.

In statistical models, the weather is considered as a special input in agricultural production as it cannot be controlled in natural setups, and is therefore regarded as an exogenous variable. Thus, the weather acts like a "natural experiment" (Angrist and Krueger, 2001, via Auffhammer et al., 2013). researchers can only observe the output of the experiment without being able to manually control for the amount of the natural input. However, the causal effects of the weather on crop yields can be examined, and has already lead a great deal of studies to try to quantify it. However, there is no consensus on the magnitude of the effects of climate change on crop yields. Lobell et al. (2011) investigated the historical worldwide relationship between temperature and four crops: corn, rice, wheat and soybean, from 1980 to 2008. Their results suggest a negative impact of temperature on both corn and wheat yields, reducing yields by 3.8% and 5.5%, respectively, with regional heterogeneity. Their results regarding the two other crop yields are less conclusive, with global declines of -0.1% for rice and -1.7% for soybean, with gains observed in some regions cancelling out losses undergone in other regions. You et al. (2009) found similar results for wheat yields in China, between 1979 and 2000. They estimated a reduction of wheat yields by 3% to 10% due to a one degree mean growing season temperature increase. Lobell and Asner (2003) estimated the impact of increasing temperatures in counties in the United States, using data from 1982 to 1998. According to the results of the article, each additional degree of the average temperature leads to a decrease of 17% of both corn and soybean yields. Simulations of changing climate are more profoundly assessed in the literature using climate scenarios. For example, Schlenker and Roberts (2009) considered different scenarios for the United States, and concluded that warming temperatures by mid 21st century would result in a substantial decrease in both corn, cotton, and soybean yields, relative to observed yields from 1950 to 2005. More specifically, the losses would range from -30% to -46% in an optimistic scenario, and would even be more damaging in the worst-case scenario, ranging from -63% to -82%. Schlenker and Lobell (2010) used historical data in Sub-Saharan Africa to link crop yields to weather variation and then used the estimated model to assess the effects of climate change on maize, sorghum, millet, groundnut, and cassava yields. For all crops, declining yields are projected, ranging from -8% to -22% by mid 21st century relative to 1961–2000 observed yields.

All these studies consider the effects of covariables on the mean of the response variable. Some studies (*e.g.*, Chen et al., 2004; Cabas et al., 2010) suggest to use Just and Pope's stochastic production function approach (Just and Pope, 1978), therefore allowing to characterize the effects of the weather on both crop yields and their variability (McCarl et al., 2008).

One of the advantage of using statistical models rather than crop simulation models is that the former clearly state the model uncertainties by giving statistical indicators regarding the quality of the estimation, which is not the norm with crop simulation models (Lobell and Burke, 2010). However, statistical models present some caveats. Even if it is common to use multiple weather variables to estimate the variations of crop yields, this practice might cause problems of multicolinearity (Sheehy et al., 2006; Lobell and Ortiz-Monasterio, 2007), especially when weather variables are disaggregated to reflect seasonal effects. Another shortcoming of statistical models is what Mendelsohn et al. (1994) refers to as the "*dumb farmer scenario*". That is, in these models, the focus is made on one type of crop only, just like in crop simulation models, therefore considering that farmers are not able to adapt to a varying environment offering new climate conditions. Hence, statistical analysis of crop yields might not be a good tool for predicting long-term variations.

2.2 The Ricardian Framework

Crop simulating models and their statistical counterpart both fail to account for the ability of farmers to adapt to a new environment. An answer is provided by Mendelsohn et al. (1994), who suggest to look at land value instead of yields. In their pioneer work, they introduce an analysis named "Ricardian analysis" after the economist David Ricardo.

The Ricardian methodology is a hedonic model of farmland pricing that focuses on land value. The basic idea is that long run climate should be capitalized into land values. In a competitive market, the price of farm land is assumed to reflect the discounted value of all the expected future profits that can derive from it. The Ricardian approach measures the impact of climate variables on land productivity or farm land values by exploiting cross sectional differences in land use and weather patterns. It is noteworthy that climate variables are used in the Ricardian analysis, rather than weather variables. As a matter of fact, an adverse weather shock such as a storm or a drought can lead to losses on crop yields, but may have ambiguous effects on profits: on the one hand, the output can be reduced and thereby lower profits; on the other hand, in the presence of inelasticity of demand for agricultural goods, the market can adjust by raising prices, thus increasing agricultural profits. But in the long-run, profits are expected to be lowered by an adverse shift in climate (Schlenker et al., 2006). Besides, in the short-run, farmers may be vulnerable to weather shocks, but in the long-run, they can adopt new farming strategies and adjust their decisions regarding the levels of inputs in response to the climate they face. Hence, using climate variables rather than weather variables is more suitable for the Ricardian framework.

In the last two decades, the original framework has been widely applied in many countries across the world. Most previous research use cross sectional data to estimate farm values on weather variables. Extensive reviews of applications for African, Asian, South American, and US regions can be found in Mendelsohn and Dinar (2009).

In the pioneering article of Mendelsohn et al. (1994), the focus was made on US farmers, and the results highlight regional heterogeneity in the effects of climate on land values. The climate scenarios tested yield mitigated results, with winners and losers. The losses undergone by losers are however projected to be relatively lower than those projected using an analysis based on crop yields. Mitigated results are also found in Africa. For instance, Kurukulasuriya and Mendelsohn (2008) showed, using farm-level data from 11 African countries collected between 2003 and 2004, that the effects of climate change on net revenues differ between irrigated farms and rainfed-only farms. The net revenues of the formers are projected to increase up to 51% in the best-case scenario, while the net revenues of the latter are projected to fall by up to -43% in the case of a hot and dry climate scenario. Similar results between irrigated and non irrigated farms were found in China (Wang et al., 2009). In Europe, Van Passel et al.

(2016) estimated the effects of climate changes using a large sample of farms across Western Europe. Although the study highlights different regional effects, it also shows that European farms are more sensitive to projected warming than US farms.

There have been a number of criticisms of the Ricardian approach. One major weakness lies in the fact that unobservable skills of farmers are not incorporated in the analysis. This shortcoming has led some scholars to introduce time-varying data to account for the problem of omitted variables by including district or regional dummies in the model (see, *e.g.*, Schlenker et al., 2006; Deschênes and Greenstone, 2007; Kim et al., 2009; Cabas et al., 2010). Unlike crop-simulation models, the Ricardian framework does not consider the fertilizing effects of CO_2, yielding biased results. Another weakness of the Ricardian model lies in the fact that it does not incorporate price effects. In the Ricardian approach, the variation in land values over climate zones is due to changes in climate variables. A strong assumption is that input and output prices remain unchanged. Special attention should be done on that point as crop prices tend to be more volatile (Cline, 1996; Schlenker et al., 2005).

Finally, the model implicitly assumes that farmers do not face adjustment costs. Hence, Ricardian results should be considered as a lower-bound estimate of the costs of climate change (Quiggin and Horowitz, 1999).

2.3 A Global Analysis of the Economic Impacts

Instead of focusing solely on the agricultural production function, a substantial number of studies rather assesses the impacts of climate change on the economy. Some attempts are made either at the global scale or on more specific geographical areas.

Studies considering the global economy highlight the existence of winners and losers under new conditions reflecting climate change. A widely used methodology consists in predicting the response of crop yields to projected climate scenarios. These scenarios are commonly given by a general circulation model (GCM), *i.e.*, a climate model. Then, the predicted agricultural yields are fed into a general equilibrium model that evaluates agricultural production as well as crops prices. It is also possible to address food security issues by assessing the number of people at risk from hunger, depending on the population, on the agricultural production and on crops prices. Rosenzweig and Parry (1994) provided a famous contribution to this literature. They identified a distinction between developing and developed countries, the former being more vulnerable to climate change than the latter. This distinction is a common result in the literature (see *e.g.*, Parry et al., 2004; Fischer et al., 2005), due to the predominance of agriculture in developing countries (Tubiello and Fischer, 2007). Another explanation to this result is that developing countries are disproportionately placed at low latitudes or near the tropics, where climate conditions are not optimal for farming activities, due to high variability in the weather.

Another way of looking at the global effects of climate change on the economy is to use another type of general equilibrium approach called Integrated Assessment Models (IAMs). IAMs are mathematical models that combine in a same framework knowledge about climate, economics, demographics and political decisions that influence greenhouse gas emissions (see, *e.g.*, Nordhaus, 1991; Nordhaus, 1994; Nordhaus and Yang, 1996; Tol, 2002). These models evaluate the social cost of carbon, *i.e.*, the monetary estimate of the damage caused directly or indirectly by the emission of a tonne of CO_2, by assessing changes in welfare due to new climate conditions. The mechanism relies on the existence of a damage function that links temperature to GDP, such that an increase in temperature might be harmful to the global production. IAMs can be used as a tool for policy analysis, by submitting different climate scenarios to the model and by modelling different policies based on the social cost of carbon. IAMs, as any other tool, come with shortcomings. One of them concerns the damage function. As stated by Weitzman (2010), the damage function is "*a notoriously weak link in the economics of climate change*", because assumptions need to be made regarding the functional form of the damage function, and because these assumptions can greatly modify the conclusions drawn using IAMs. Pindyck (2013) also noted that IAMs fail to account for catastrophic weather outcomes, which might have very large impacts.

A lot of studies focus on more specific geographical areas. The distinction between developing and developed economy still holds for these studies, as the challenges faced by developing countries are somewhat different that that faced by developed countries.

In developing countries, the agricultural sector usually represents an important share of the national GDP. These countries are thus heavily dependent on their agricultural sector, so that poor weather conditions may have substantial impacts at the national level. An adverse weather shock affecting the agricultural production may create a situation of food shortage leading to an increase in prices. In 2016, Southern African countries were hit by a second consecutive season of drought resulting in crop failure. According to the FAO, the consequences are dramatic, exposing almost 40 million people to food insecurity. In the same year, many Indian states also suffered from massive droughts coupled with weak monsoon. It created a water shortfall affecting the agricultural production and leading to an increase in prices. The economic situation of millions of people was therefore threatened in India, a country in which about half of the population works in the agricultural sector.

With climate change, the number of extreme episodes that have seriously negatively affected developing countries in the past is expected to increase. Depending on the intensity of climate change, people in developing countries may need to adapt to their new climate environment. Many papers thus look at possible adaptation undertaken by farmers that may help mitigating the negative effects of climate change on food production. For example, Butt et al. (2005) showed that adopting new farming techniques, mixing crops or more heat-resistant varieties of crops may help farmers in Mali to better cope with climate change and mitigate the overall damages caused by climate change. Di Falco et al. (2011) found that farm-households that adapted to a changing climate tend to produce more than farm-households that did not adapt, and that access to credit as well as information provision regarding climate are important determinants of the adaptation. If the costs of adaptation are too high, people facing too adverse weather conditions might be forced to emigrate, as shown by Black et al. (2011).

In high-income countries, where the agricultural sector is not as important in terms of GDP, the challenges are somewhat different but also deserve to be carefully investigated. Countries like the United States of America, Australia, or members of the European Union, are key actors of world agricultural markets. According to the FAO, during the last three years, around 40% of global cereal production came from developed countries (FAO, 2017), mostly from North America and Europe. Developed countries are often leading producers on agricultural markets. Hence, weather accidents may greatly affect world production and generate food security troubles. In 2003, the summer average temperature in Europe was up to 6°C above its average 1998–2002 mean and precipitation were 50% below the average (Ciais et al., 2005). Western European countries were severely impacted by the heat wave that summer, with an increase in mortality and in forest fires. The agricultural sector also suffered from the heat wave: compared to the previous year, crop production decreased by 36% and 30% in Italy and France, respectively; the fodder deficit was of the same order (Easterling et al., 2007); 4 million broilers died and milk production was reduced (García-Herrera et al., 2010). A few years later, in 2012, the United States also underwent an extreme negative weather shock which affected its corn production. According to the United States Department of Agriculture, crop production dropped by 13% compared to the previous year. As the United States are the exports leaders in global corn exports, and since the world corn reserves were low at that time, the decrease in production impacted world corn prices, that rose by 25% to reach a peak even higher than the one recorded during the 2007–08 food price crisis (Chung et al., 2014). Hence, when these countries experience poor weather conditions, it can negatively affect their production and lead to an increase in prices, which can in turn create disturbances regarding food security.

Therefore, weather conditions affect developing countries and developed countries in a different way.

3 Outline of the Thesis

This thesis is intended to be a contribution to the theoretical and empirical debate regarding climate change and agriculture. It is structured into two parts containing four complementary essays that employ a variety of econometric and theoretical methods allowing to account for the main features of the countries studied.

The first part of the thesis consists of two microeconomic analyses for a developing country, India, focusing first on the supply side and then turning to the demand side of the agricultural production. The second part concerns developed countries. It starts with a regional study applied on western Europe regions, *i.e.*, in regions of countries with a significant impact on agricultural world market. The final step highlights the interest in considering a general equilibrium approach to examine the interactions that take place between the agricultural sector and the rest of the economy, in the context of a small-open economy, applied on New Zealand data.

Chapter 1, entitled "***Climate Change and Profits: a Ricardian Analysis***", looks at individual decisions of farmers in a developing country in which the agricultural sector represents a non-negligible share of the national economy. The purpose is to understand the effects of weather variability on Indian farming profits, and to examine the potential effects of climate change on these profits, under different climate scenarios. The analysis in the first chapter adopts the Ricardian approach that links net revenues per acre as a function of climate, farm and households characteristics. The function of net revenues per acre is estimated using detailed cross-sectional data. While most studies on Indian agriculture are conducted on district-level data, this study is carried out at the individual farm-level. The spatial distribution of the observations allows for a fair coverage of the whole country, relying on $7,751$ individual observation within

202 districts, therefore providing generalisable results at the Indian scale. The mechanisms explaining the variations of net revenues per acre are examined using quantile regression, thus allowing a deeper understanding of the impacts of climate variations on the distribution of net revenues per acre.

Empirical results show that farms with higher net revenues per acre look to be more affected by weather variables in magnitude. Farms with lower net revenues per acre tend to benefit more from crop mixing than farms with high income per acre. In a second step two climate scenarios which differ according to the assumptions on changes on average temperature and total rainfall are envisaged. Farms with low net revenues per acre experience losses less important in magnitude but larger in percent change than farms with high net revenues per acre. At the district level, results show more heterogeneity. Under both scenarios, districts in the North of India tend to experience a decrease in net revenues per acre while an opposed effect is found for districts in the South of the country.

Chapter 2, entitled "***Climate Change and Food Security: a Farm-Household Model***", uses the results of the first chapter as a starting point. We previously found heterogeneous effects of climate on profits among farmers, depending on the type of households. In the second chapter, the effects of weather variation on both agricultural production and consumption expenditures are investigated for different types of farm households, depending on their labour market participation. As a first step, the study evaluates the effects of climate variations on the agricultural production of Indian farm households. Then, the results of the first step are used to estimate an Almost Ideal Demand System for different types of farm households classified according to their labour regime. Different scenarios on prices as well as on climate variables are then tested to assess the underlying effects on decision consumptions. As in the first chapter, the study uses data at the individual farm level with a good spatial coverage of India. In addition, the analysis complements the view given in chapter 1 by exploring both the supply and the demand side of farm households.

We find that the agricultural production is sensitive to both temperature and rainfall. Consumption decisions are also affected by climate conditions. In particular, an increase in total rainfall leads to a higher demand for pure market goods and animal derived products, and a decrease in crops and leisure. In addition, crops demand is more affected by the variation in rainfall for autarkic households relative to other types of rural households. On the contrary, the demand for crops products of autarkic households is less affected by varying temperatures. The scenarios in which both rainfall and temperatures are changed exhibit a trade-of between crops and animal-derived products.

Chapter 3, entitled "***Climate Change and Agricultural Yields: an European Case Study***", considers a more aggregated view, for western Europe countries, *i.e.*, developed economies. Moreover, a time dimension is introduced in contrast to the two previous analysis. This additional feature allows us to introduce the question of the volatility of prices, which has been a fundamental issue in agricultural markets in the recent years, although frequently ignored in the literature. The volatility of prices is in fact a key issue for European countries, especially in the context of the abandonment of price support for farmers in the Common Agricultural Policy (CAP). The third chapter incorporates the volatility of production prices in an attempt to study the relationship between weather variations and yields of two major crops, *i.e.*, wheat and corn. The effects of climate change on European agriculture under different alternative scenarios are empirically studied.

Empirical results exhibit the effects of seasonal weather variables on both mean yields and the variance of wheat and corn yields. Prices show a positive and significant impact on wheat yields for northern Europe, only after the CAP reform. Prior to this reform, the effect of prices on yields were not statistically different from zero. The empirical models are then used to assess the effect of climate change on yields. Four climate projection scenarios reflecting greenhouse gas concentration trajectories are tested. Mitigate spatio-temporal effects are found. Wheat yields would increase at the European scale under most scenarios, but the gains would decrease with time for regions in the north in the long-run. Results are less optimistic for corn yields. In the short-run, some northern regions would experience gains in yields, but these gains would transform into losses in the long-run. Those losses would even be higher in the south of Europe.

Chapter 4, entitled "***Climate Change and Business Cycles***", provides a general equilibrium approach, unlike the first three chapters that are based on a partial equilibrium framework. The aim of this last chapter is to investigate the influence of weather shocks on business cycles, through an estimated dynamic model for a small open economy. An original DSGE model with a weather dependent agricultural sector is developed and estimated using Bayesian methods and quarterly data for New Zealand over the sample period 1989 to 2014.

The results from the model suggest that weather shocks play an important role in explaining macroeconomic fluctuations over the sample period. A weather shock – as measured by a drought index – acts as a negative supply shock characterized by declining output and rising prices. In addition, the results show that farmers do not anticipate weather shocks and are mostly surprised by variable climatic conditions. Finally, increasing the variance of climate shocks in accordance with forthcoming climate change leads to a sizeable increase in the volatility of key macroeconomic variables, such as production and inflation.

Part I

Climate Change in Developing Countries: the Indian Case

The first part of this thesis is devoted to the analysis of the effects of climate change on developing economies. The focus is empirically made on an emerging economy, namely India. India is located in Southern Asia and is the second most populated country in the world after China, according to the United Nations, with an estimated population of 1.33 billion in 2016. India is the 7th largest nation in the world with a total area of 3.29 million square kilometres. According to the World Bank, around 60% of Indian's land is devoted to agriculture. Agriculture is an important economic sector of India, although its share in GDP has declined over years, falling from around 42% of GDP fifty years ago to 17% in 2015. Even if the value added of agriculture in GDP is not as high as it used to be, almost one in every two workers is employed in the agricultural sector. In addition, since the early sixties, food grain production in India increased more than threefold – from 87 million tonnes in 1961 to 295 million tonnes in 2014, as reported by the FAO. This increase in production was made possible thanks to the Green Revolution that started in the early 1960s, with the introduction of higher-yielding varieties of crops, improving water schemes, and increase use of chemical fertilizers. This enabled India to achieve food self-sufficiency and even to become a net food exporter.

The question of agricultural sustainability emerges as an important concern for India. Food self-sufficiency may be challenged in the near future by the growing population in the country. Furthermore, the increase in crop yields observed during the last decades might not be as spectacular over the coming years. In addition, climate change places a real sword of Damocles over Indian food autonomy. The number of farms that rely on precipitation as the only source of water for their agricultural production is still substantial (around 40%), making production highly vulnerable to weather variations. The increasing average temperature coupled with enhanced occurrence of droughts that are expected due to climate change might offer inadequate climate conditions for certain varieties of crops, therefore adding uncertainty on agricultural production.

The first part of this thesis provides two empirical analyses at the scale of rural households in India. The first chapter examines the relationship between farmers' profits and weather variations, and identifies how farmers may be impacted by climate change depending on the relative magnitude of their profits and also depending on their geographical situation. The results of this first analysis are the starting point of the second study. Climate conditions in some Indian regions are more conducive to agricultural activities than others, and the projected climate change scenarios of the first study highlight heterogeneous responses in farmer's net revenues. It may be interesting to enlarge the picture offered in chapter 1 by considering both the supply and the demand side of agricultural production. From the supply side, the impacts of climate change might create food shortages and threaten food sufficiency. From the demand side, the consumption decisions might depend on climate, especially in the context of a developing country, in which a great number of rural households consume a substantial share if not all of their production. Chapter 2 investigates these aspects.

Chapter 1

Climate Change and Profits: a Ricardian Analysis

Joint work with Catherine Benjamin (University of Rennes 1

1 Introduction

The prospect of substantial climate change and its potentially huge impacts are central concerns for the scientific community and policy makers. Research on climate impacts has grown considerably since past years, and much has been learned regarding the potential risk of damage associated with projected climatic change.

Climate change is expected to increase the variability of weather conditions and the frequency of extreme weather events. Results from an International Panel on Climate Change (IPCC) study predict increasing temperatures will lead to an increase in the number, and severity, of extreme climates events like tornadoes and heavy rainfall in some regions, and droughts in others (Edenhofer et al., 2014). Because food production is fundamentally a biological process that depends in part, of temperature and moisture, the agricultural sector's potential vulnerability is particularly large.

There is an ongoing scientific debate over the magnitude of the effect of climate change on overall agricultural sector. This debate partly stems from countervailing effects of climate change, which makes possible the potential for increased production in the short-run, and producers' ability to adapt locally and globally through changing agricultural practices, shifting crop production, research and development and increase trade. Some of the crucial inputs needed are the answers to the following questions: How will climate change affect agricultural production? How will it change variability of yields? How, and under what circumstances, will climate change increase and/or reduce production? In affected regions and countries, how difficult will it be for producers to shift to different crops, to adopt new cropping patterns, and to adjust production practices to the new environment?

The economic impacts of climate change on agriculture have been studied extensively world over and in developing countries. Mixed effects are found by previous empirical research.

Lobell et al. (2011) found that over the years 1980–2008, temperature trends were higher than one standard deviation of historic variability in most countries. Tol (2009) argued changes in weather patterns can have deleterious effects on agriculture, with low-income countries being especially vulnerable to its effects. Deschênes and Greenstone (2007) considered the effects of changes in temperature and precipitation on agricultural land rents, and conclude that climate change could lead to a slight increase in U.S. corn and soybean profit, although Fisher et al. (2012) found higher potential impacts of climate changes on US agriculture. Mendelsohn et al. (2006) found that poor countries suffer much more from climate change than do rich countries. Further analysis reveals that these adverse impacts stem from two factors. First and foremost is the fact that the low income countries are disproportionately placed in the tropics, where temperatures are already above the optimum for many crops. Thus, further temperature increases bring large crop losses, whereas they bring gains in the higher latitudes. Secondly, since agriculture is found as the most severely affected sector, the relatively heavier reliance of these poor countries on farming results in larger losses as a proportion of GDP.

A result shared by different studies is that the negative impacts of climate change are more severely felt by poor people and poor countries. Developing countries, particularly the least developed countries, look to be more vulnerable because of their high dependence on natural resources, and their limited capacity to cope with climate variability and extremes climatic events.

This chapter tries to provide empirical estimate of the impact of climate change in India. India is chosen for two major reasons. First agriculture is an important sector of Indian economy. According to the World bank, this sector represented 17.4% of the value added to GDP in 2014, and employed 49.7% of the workforce in 2013. This sector is particularly vulnerable to present-day climate variability, including multiple years of low and erratic rainfall. Scenarios generated by climatic models show that India could experience warmer and wetter conditions as a result of climate change, particularly if the summer monsoon becomes more intense (Mitra et al., 2002; Rupa Kumar et al., 2002; McLean et al., 1998). About a quarter of India's land is turning to desert and degradation of agricultural areas (source, environment minister, 2014).

Secondly, India is one of the fastest growing economies of the world and is currently the focus of a great deal of international attention. In 2015, the population of India amounts to nearly 1.311 billion, which makes it the second most populous nation in the world. The country has today emerged as a major player in the global agriculture market. The leading forecasting institutions (OECD, FAPRI) expect that India will play a bigger role in world markets in future. Weather fluctuations are potential sources of threatening food security. In fact, "*under normal weather conditions, domestic output levels of rice and wheat in India are nearly sufficient to meet the domestic demand for these grains. Due to weather fluctuations, the country faces a situation of deficit in some years and surplus in some others and thus it is neither a regular importer nor exporter*" (Srinivasan and Jha, 2001). The unprecedented 2007–2008 world food price crises, when agricultural prices have been highly volatile soured partly due to decreased supply and increase demand is a clear example of world challenge. The demographic and economic growth of emerging countries (for instance in India) and adverse weather conditions were defined as some of the various factors which contributed to this observed huge volatility.

This study uses the Ricardian approach to estimate the sensitivity of Indian farms to climate conditions. This analysis, compared to previous ones on Indian agriculture, uses cross-sectional individual data on farms to estimate the impact of climate and household variables on net crop revenues.

In India, previous studies on Indian agriculture are mainly conducted on district-level aggregate data (Kumar and Parikh, 1998, 2001; Sanghi and Mendelsohn, 2008). In case of cross-sectional studies, they are focused on specific regions which may lack generalization.

According to Mendelsohn (2008), the first attempt to assess the impact of climate on net revenue in developing countries at the farm level concerns 11 countries of Africa (Kurukulasuriya et al., 2006). Wang et al. (2009) also used farm-level data in China.

Furthermore, this analysis contributes to the existing knowledge in India by using quantile regression. Most of the empirical studies use standard linear regression techniques to summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function. This approach provides only a partial view of the relationship, as we might be interested in describing the relationship at different points in the conditional distribution of the dependent variable (here, net revenues per acre).

This first chapter is organized as follows. Section 2 encompasses discussions on the specification and of the individual equations. Data are presented in section 3. Empirical results are discussed in section 4. Section 5 provides climate scenarios exercises. Some policy relevant observations emerging from this study are summarized in section 6.

2 Modeling Net Revenue

This study is based on the Ricardian approach developed by Mendelsohn et al. (1994). In this section, we will briefly present the Ricardian framework and then the quantile regression methodology.

2.1 Behavioural Model: the Role of Climatic Variables

The Ricardian analysis investigates the link between farm value – or net revenue (see, *e.g.*, Deressa et al., 2009; Gbetibouo and Hassan, 2005; Haim et al., 2008; Kumar and Parikh, 1998; Sanghi et al., 1998) – and climate, soils, demographic, and economic variables. The idea behind this framework is that farmers have adapted their behaviour to face their environment.

The assumed objective of each farmer is to maximise his income subject to some constraints. In this sense, the farmer from exploitation i decides for each crop $j \in J$ and for each input $k \in K$ the level of the input X_{ikj} in order to maximise net revenue (Dinar and Mendelsohn, 2011) :

$$\max_{X_{ikj}} \pi_i = \sum_{j \in J, k \in K} \left[p_j F_j(X_{ikj}; E_i, W_i, Z_i) - w_k X_{ikj} \right], \tag{1.1}$$

where π_i is the net revenue for farm i, p_j and w_k are vectors of output and input prices respectively, that producers take as given. The production function associated with each crop is denoted by $F_j(\cdot)$, and is a function of input choices X_{ikj} given exogenous environment conditions, *i.e.*, economic control variables E_i, climate variables W_i and farm specific variables Z_i. The set of inputs that maximises net revenue is obtained by differentiating eq. (1.1) with respect to each input, and gives the Ricardian function:

$$\pi_i^* = \pi_i(E_i, W_i, Z_i \mid p_j). \tag{1.2}$$

Land value (V_i) for farm i will equate the present value of the net revenue of each farm, assuming perfect competition for land (Deschênes and Greenstone, 2007):

$$V_i = \int_0^\infty \pi_{j,t}^* e^{-rt} \, \mathrm{d}t, \tag{1.3}$$

where r is the market interest rate. Then, exploring the relationship between net revenue and climate enables to quantify the impact of the latter on the present value of net revenue (Mendelsohn et al., 2001). However, in developing countries where land market are imperfect, Ricardian analysis do not use land value as the dependent variable. Instead, net revenues per unit of area are used (see, *e.g.*, Gbetibouo and Hassan, 2005; Sanghi and Mendelsohn, 2008).

Empirically, eq. (1.3) is estimated with a linear model of the following form (see, *e.g.*, Sanghi and Mendelsohn, 2008; Kumar and Parikh, 2001; Polsky, 2004):

$$V = \alpha + \boldsymbol{\beta}^\top \boldsymbol{E} + \boldsymbol{\gamma}^\top g(\boldsymbol{W}) + \boldsymbol{\zeta}^\top \boldsymbol{Z} + \boldsymbol{\varepsilon}, \tag{1.4}$$

where V is the annual net revenue per unit of land, $\boldsymbol{E}$ is a set of economic variables, $\boldsymbol{W}$ is a matrix of climatic variables, $\boldsymbol{Z}$ is a matrix of farm specific characteristics, $\boldsymbol{\varepsilon}$ is a standard error vector, and α, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\zeta}$ are parameters that need to be estimated. The function $g(\cdot)$ allows non-linear effects of climate on net revenues to be taken into account. A common practice is to introduce linear and quadratic terms for each climatic variable (see, *e.g.*, Schlenker et al., 2006; Fleischer et al., 2008; De Salvo et al., 2013; Deressa et al., 2009).

However the Ricardian analysis offers the advantage to implicitly assume that farmers adapt to their environment, this methodology has some drawbacks. In the original work of Mendelsohn et al. (1994), the question of irrigation is deliberately left aside. This choice has been criticized in the literature (Cline, 1996; Schlenker et al., 2005). In fact, irrigation is a choice that is sensitive to climate. To overcome this criticism, some authors choose to introduce a variable related to irrigation. A dummy variable indicating whether the farm is irrigated or not might be used (Kurukulasuriya and Mendelsohn, 2008), or whether the farm has access to an irrigation technique (Deschenes and Kolstad, 2011). The percentage of land under irrigation might also be used (Polsky and Easterling III, 2001; Gbetibouo and Hassan, 2005; Barnwal and Kotani, 2013). It is also possible to analyze the effects of climate conditions either on rainfed farms or on irrigated farms, separately (Schlenker et al., 2006; De Salvo et al., 2013; Van Passel et al., 2016). We first address the question of irrigation by introducing a variable indicating if the farm is irrigated, and if so, which kind of irrigation technique is used. We also compare the sensitivity of net revenues per acre to climate conditions on either rainfed farms or irrigated farms.

The Ricardian model also suffers from its assumption of constant prices resulting from the use of cross-sectional data. According to Cline (1996), this leads to a bias in the analysis and thus to biased estimations of the global damages or benefits of global warming. The same problems appear with the absence of consideration of the positive impact of carbon dioxide fertilization highlighted by field experiments (Parry et al., 2004; Aggarwal and Mall, 2002).

2.2 The Empirical Approach: the Use of Quantile Regression

The aim of this study is to estimate eq. (1.4) for India, using cross-sectional data. Most studies consider the impact of climate on the conditional *mean* of net revenue given some values of the independent variables, and assume a parametric distribution for the error term. But there might be some asymmetry in these impacts across the quantiles of net revenues. Quantile regression is one way to get to the bottom of these possible asymmetries (Barnwal and Kotani, 2013). Also, as pointed-out by Van Passel et al. (2016), quantile regression offers estimations that, compared to OLS, are more robust to outliers.

Quantile regression was introduced by Koenker and Bassett Jr (1978). The τ^{th} quantile of a real-valued random variable V is given by:

$$Q_V(\tau) := F^{-1}(\tau) = \inf\{v : F(v) \geq \tau\}, \tag{1.5}$$

where $F_V^{-1}(v)$ is the inverse of the distribution function $F_V(v)$ of V and τ can be any value in the interval $(0, 1)$.[1]

The τ^{th} conditional quantile function is (Koenker, 2005):

$$Q_V(\tau \mid \boldsymbol{X}) = \boldsymbol{X}^\top \boldsymbol{\beta}_\tau, \tag{1.6}$$

where $\boldsymbol{X}$ is a set of explanatory variables. An estimator of $\boldsymbol{\beta}_\tau$ can be obtained by solving:

$$\underset{\beta \in \mathbb{R}^p}{\text{argmin}} \sum_{i=1}^{n} \rho_\tau(v_i - x_i^\top \beta), \tag{1.7}$$

where $\rho_\tau(\cdot)$ is a loss function defined as

$$\rho_\tau(u) = u(\tau - \mathbb{1}_{\{u<0\}}). \tag{1.8}$$

The model writes:

$$V(\tau \mid \boldsymbol{E}, \boldsymbol{W}, \boldsymbol{Z}) = \alpha_\tau + \boldsymbol{\beta}_\tau^\top \boldsymbol{E} + \boldsymbol{\gamma}_\tau^\top g(\boldsymbol{W}) + \boldsymbol{\zeta}_\tau^\top \boldsymbol{Z} + \boldsymbol{\varepsilon}_\tau, \tag{1.9}$$

$$\text{where } Q_V(\tau \mid \boldsymbol{E}, \boldsymbol{W}, \boldsymbol{Z}) = \alpha_\tau + \boldsymbol{\beta}_\tau^\top \boldsymbol{E} + \boldsymbol{\gamma}_\tau^\top g(\boldsymbol{W}) + \boldsymbol{\zeta}_\tau^\top \boldsymbol{Z}, \tag{1.10}$$

where V is the annual net revenue, $\boldsymbol{E}$ is a set of economic variables, $\boldsymbol{W}$ is a matrix of climatic variables, $\boldsymbol{Z}$ is a matrix of farm specific characteristics, $\boldsymbol{\varepsilon}_\tau$ is a standard error vector for a quantile τ, and α_τ, $\boldsymbol{\beta}_\tau$, $\boldsymbol{\gamma}_\tau$ and $\boldsymbol{\zeta}_\tau$ are parameters that need to be estimated for the set of quantiles. Function $g(\cdot)$ is a two-degree polynomial.

3 Data

To assess the impact of climate and other variables on net revenues across farmers in India, this study relies on two data sources. Some descriptive statistics are provided in table 1.2.

[1] In our analysis, we choose to estimate the vector of coefficients $\boldsymbol{\beta}_\tau$ at 17 quantiles, from $\tau = 0.1$ to $\tau = 0.9$ by increments of 0.05. This arbitrary choice allows to draw smooth curves in section 4. However, for clarity purposes, we only report result at three quantiles ($\tau = \{0.25, 0.5, 0.75\}$) in the tables and in some graphs.

3.1 Household Survey

The *Indian Human Development Survey* (IHDS) (Desai et al., 2005) is a nationally representative survey conducted in India between 2004 and 2005. It was organized by researchers from the University of Maryland and the National Council of Applied Economic Research. Besides information about socio-economic conditions of the respondents, the IHDS gives numerous details on agricultural activities of households, such as farm structure, expenditures and revenues. Unfortunately, locations for each household can only be traced at the district level.[2]

In our analysis, only households that report at least one worker in the farm and declare that they cultivate crops are considered, the others are discarded. When information about education is missing, data are removed as well. Individuals lying in mountain regions of India[3] are removed, since our estimations for climate variables are subject to high variation in those areas. Finally, to have more consistent estimators, districts with less than 20 observations are excluded. In the end, the analysis relies on $7,751$ individuals within 202 districts (see fig. 1.1).

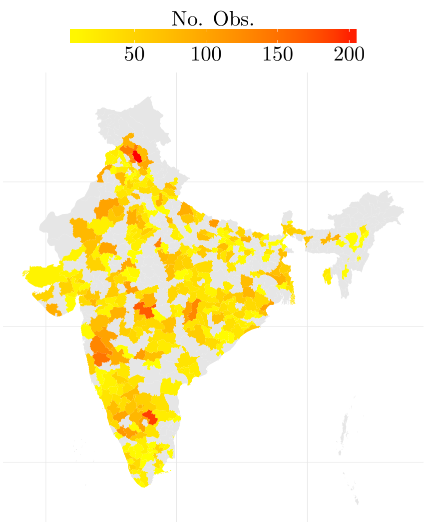


Figure 1.1: Number of Observations per District

Explanatory variables are divided in four groups: personal characteristics, farm characteristics, location characteristics, and climatic factors.[4]

[2]See Desai et al. (2010) for more details.

[3]It concerns only three states in this data set: Arunachal Pradesh, Jammu and Kashmir, and Meghalaya.

[4]A description of each variable used in the analysis is provided in appendix A.

3.2 Measure of the Climatic Variables

To investigate the impact of climate on agricultural net revenue, it is common practice to use "climate normals". "Climate normals" are the average of weather variables over a prolonged period of time (see, *e.g.*, De Salvo et al., 2013; Kumar and Parikh, 2001; Polsky and Easterling III, 2001). As reminded by Schlenker et al. (2006), one needs to distinguish between weather and climate: the weather refers to meteorological conditions at a given moment while climate considers an average of climate statistics over an extended period of time. With cross-sectional data, using "climate normals" offers the advantage of implicitly taking into account the adaptation response of farmers to local climate (Di Falco et al., 2011).

Unfortunately, there is no information about meteorological conditions in the survey data. So, this study relies on daily temperature and precipitation obtained from 112 weather station[5] for the 30-year period from 1976 to 2005. Data are provided by National Climatic Data Center (NCDC)/National Oceanic and Atmospheric Administration (NOAA). As net revenues per acre are given at the district level, weather data need to be aggregated at the same spatial level before considering computing "climate normals".

A four step procedure is followed.[6] First, some missing data are estimated, using a weighted average based on past and future observations. Then, a spatial interpolation technique called *thin plate splines* (see, *e.g.*, Di Falco et al., 2011; Boer, 2001; Hutchinson, 1995) is employed to obtain estimations of weather data at each point of a grid covering the whole country. Once the estimation for each cell of the grid is performed, an average by district can easily be computed. It is then possible to aggregate data by season and district, in a fourth step. Four seasons are defined here: (i) *Winter* (January to March) (ii) *Summer* (April to June), (iii) *Monsoon* (July to September), and (iv) *Autumn* (October to December).

3.3 Geographic and Soil Characteristics

To account for soil quality heterogeneity, we add a set of soil characteristics variables from the Harmonized World Soil Database (Batjes et al., 2008). We rely on a different set of variables, aggregated at the district level.

[5]See appendix A for a spatial distribution of the weather stations.
[6]The procedure is more detailed in appendix A.

Population density is also added at the district level to our database. The values are obtained from the Census 2011, a national census survey conducted in all states of the country.

It might be interesting to add information relative to the distance of the farm to the nearest market center, to proxy transaction costs. Unfortunately, the exact location of each farm is not provided in the database.

3.4 Descriptive Statistics

Table 1.2 summarizes descriptive statistics for the whole sample (first column) and for two sub-samples based on net agricultural revenues per acre: the 25% observation with lowest revenues per acre (second column) and 25% observations with highest ones (third column).

The variable of interest is the annual agricultural net revenues per acre. As shown in Table 1.2, the average value equals $5,214.95$ rupees per acre. The distribution of these revenues is skewed on the right.[7] Hence, most farms of the sample have modest revenues, but some farms perform way better. If one focuses on the sub-sample of the 25% lowest revenues on the one side, and on the sub-sample of the 25% highest revenues on the other side, one can see quite a difference in the averages: -647.78 rupees per acre for the former and 15091.92 rupees per acre for the latter.

A positive effect of age and years of schooling is expected on net revenues. This effect should be different for farms with low revenues and for farms with high revenues. Indeed, head of households' average age and years of schooling are greater for farms with higher net revenues.

Most farms in the sample work on quite small surfaces, lower than 5 acres, though a few individuals operate on large exploitation, which rises the mean value of the sample. Moreover, farms with high revenues per unit of land also have higher cultivated surfaces than farms with low ones.

Farms with higher income per acre also tend to have more bullock carts, more tractors, and more workers than farms with lower net revenues per acre. Farmers with higher net revenues also tend to diversify their cultures. This use of crop mix is expected to have a positive effect on agricultural revenues, as they enable a diversification of risk.

[7] See in appendix A for a representation of the distribution of net revenues per acre.

A large part (40%) of the sample does not use any irrigation system (table 1.1). For farmers who benefit from irrigation source, there exists different irrigation schemes, the most important of which is the use of tube wells. A positive effect of any irrigation system is expected on net revenues, as opposed to the situation where the farm is not irrigated.

TABLE 1.1: Irrigation Techniques in the Sample

	None	Tubewell	Other well	Gov.	Tank/ Pond	Other	Private canal
No Obs.	3102	2577	892	455	377	222	126
Percentage	(40.02%)	(33.25%)	(11.51%)	(5.87%)	(4.86%)	(2.86%)	(1.63%)

Finally, it is noteworthy that in the database, precipitation in summer and in autumn is lower for farms with low revenues than farms with high revenues. However, summer and autumn temperatures values are not significantly different in the two sub-samples, according to a Welch Two Sample t-test.

TABLE 1.2: Summary Statistics for Data Set on Farm Households

	Arithmetic Means and Standard Deviation		
	Whole sample (n=11639)	Lowest 25% of net ag. revenue (n = 2910)	Highest 25% of net ag. revenue (n = 2910)
Variable of interest			
Net agricultural revenue (rupees per acre)	5214.95	-647.78	15091.92
	(18810.32)	(3936.73)	(35456.49)
Climate variables (30-year average)			
Summer precip. (mm)	24.69	21.89	30.78
	(15.34)	(12.31)	(20.51)
Autumn precip. (mm)	12.4	12.62	14.23
	(9.37)	(10.25)	(11.09)
Summer temp. (^oC)	30.58	30.82	29.89
	(1.79)	(1.76)	(1.8)
Autumn temp. (^oC)	22.66	22.95	22.6
	(2.13)	(2.01)	(2.48)
Personal characteristics			
Age of head of household (years)	49.89	48.97	51.64
	(13.39)	(13.65)	(13.48)
Literacy (years of schooling)	7.23	6.3	8.86
	(4.72)	(4.78)	(4.44)
Farm characteristics			
No. bullock carts	0.22	0.12	0.38
	(0.42)	(0.34)	(0.5)
No. different cultures	2.67	2.07	3.42
	(1.5)	(1.23)	(1.58)
No. workers in the farm	2.49	2.29	2.8
	(1.27)	(1.15)	(1.49)

Continued on next page

Table 1.2 – continued from previous page

	Arithmetic Means (standard deviation)		
	Whole sample (n=11639)	Lowest 25% of net ag. revenue (n = 2910)	Highest 25% of net ag. revenue (n = 2910)
Area planted (acre) (acre)	6.24	3.56	12.94
	(10.62)	(7.15)	(17.52)
Geographic and soil characteristics			
Latitude (degree)	22.19	21.29	22.9
	(5.4)	(5.69)	(5.63)
Longitude (degree)	78.96	78.24	79.2
	(4.6)	(4.01)	(5.56)
Pop. density (hab/m^2)	384.55	382.5	377.07
	(293.01)	(282.64)	(311)
Gravel Content (%vol.)	8.52	8.55	8.25
	(2.84)	(2.71)	(2.91)
Sand Fraction (%wt.)	39.55	39.35	37.92
	(10.28)	(9.93)	(10.1)
Silt Fraction (%wt.)	30.33	30.03	31.11
	(4.91)	(4.74)	(4.68)
Clay Fraction (%wt.)	29.66	30.17	30.62
	(9.79)	(9.41)	(10.16)
pH (H2O) ($-\log(H^+)$)	6.83	6.83	6.98
	(0.67)	(0.57)	(0.7)
Calcium Carbonate (%weight)	1.91	1.67	2.46
	(2.12)	(1.77)	(2.46)
Sodicity (%)	2.47	2.28	2.94
	(1.88)	(1.67)	(2.21)

Notes: observations are averaged on the whole sample (first column), on the sub-sample of the 25% lowest net agricultural revenue per acre (second column), and on the sub-sample of the 25% highest net agricultural revenue per acre (third column). Standard deviations are reported in brackets below the average value.

4 Results

The determinants of the variations of net agricultural profit per acre are estimated by OLS (eq. 1.4) and at different quantiles using quantile regression (eq. 1.9). The results are displayed in table 1.3. Each column reports both the estimates and standard errors for a given quantile (0.25, 0.5, and 0.75), except for the last column which gives the OLS estimates.[8] Figures 1.2, 1.4 and 1.5 display the value of the coefficients of the regression at a broader range of quantiles. Finally, fig. 1.3 offers a visualization of the marginal effects of an increase in seasonal precipitation or temperature.

As we introduced quadratic and interaction terms for climate variables (as in De Salvo et al., 2013; Kumar and Parikh, 2001; Sanghi and Mendelsohn, 2008), some simulation

[8]Estimations were made at more quantiles, from 0.1 to 0.9 by increments of 0.05, but tables only show estimates for a restricted set of quantiles, because of space limitations.

were run to assess the impact of a unit change of these variables at different quantiles of the conditional net revenue distribution, holding other variables constant. Predictions computed for each individual using original data are compared to predictions made with new data, where a given variable underwent an increase of one unit. Results are shown in boxplots for each quantile considered. The same idea is applied to categorical variables, changing values of individuals with reference characteristic to another one.

4.1 Climate Effects

This section looks first at the effects of rainfall on profits per acre before investigating the effects of temperature. To avoid multicolinearity problems, monsoon and winter climate variables were discarded from the empirical model. The correlation of these variables are lower than seasonal precipitation and temperature observations with the response variable.

Estimates of linear and quadratic terms of precipitation parameters vary across the quantiles of the conditional distribution of net revenues for both summer and autumn (fig. 1.2). Hence, the impact of a variation in total rainfall is different for farms with small net annual revenues per acre (individuals at the lower tail of the net revenue conditional distribution) than it is for farms with higher annual net revenues per income (individuals at the upper tail).[9] While the OLS coefficient for summer precipitation is not statistically different from zero, quantile regressions tell a different story. The effects of summer precipitation on net profit per acre differ depending on the considered quantile. At most quantiles, the quadratic term is not significant at the 5% level. The relationship between autumn precipitation and net agricultural profit is more clear. Precipitation in autumn have an inverted-U shape relationship with net revenues per acre. That is, an increase in autumn precipitation increases profits up to a certain threshold, above which the increase in precipitation leads to losses. The value of this threshold varies according to the quantile, and is higher for farmers with smaller revenues per acre, *i.e.*, farmers at the lower tail of the distribution. In fact, the threshold value is around 30mm for those farmers, while it drops to 21mm for farmers at the upper tail of the distribution.

Looking at the overall effect of a one millimetre rise in 30-year average total rainfall for summer and autumn (fig. 1.3) gives another insight. Farms are globally positively

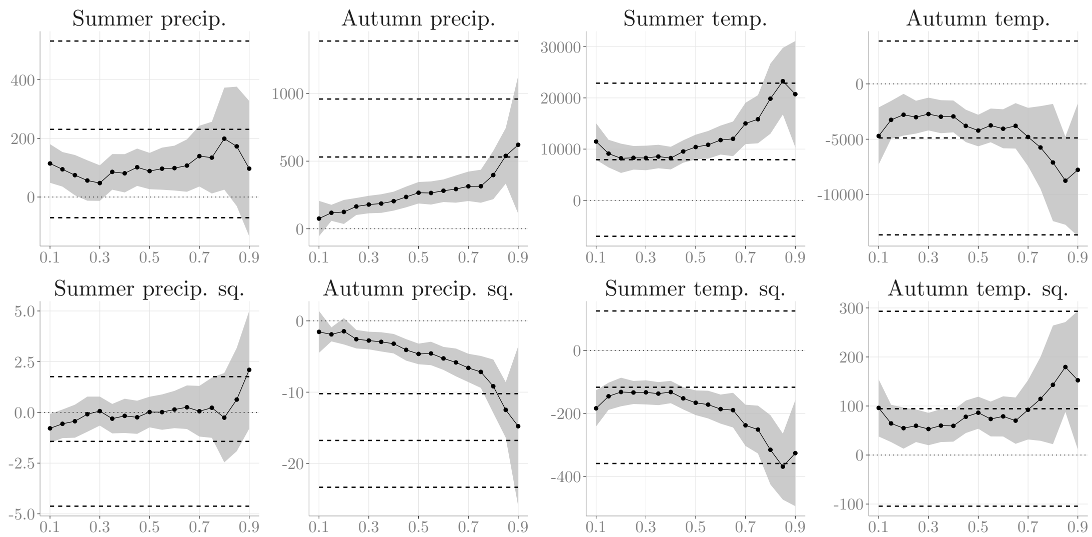
[9]Estimates for farms at the upper tail are less precise, as the confidence intervals become larger as one moves up through the conditional distribution of net revenues per acre, implying a higher variance.

affected by an increase in summer and autumn total rainfall, and the magnitude of the effect tends to be higher for farms with high net revenues per acre.

With OLS, a pure location effect in the distribution of net revenue is implicitly assumed. If this assumption were true, farms with small net revenues per acre would be affected in the same way as farms with high net revenues per acre (one would expect the estimates at each quantile to be the same). But as shown in fig. 1.2, this assumption is violated. The global effects of a one degree Celsius rise in 30-year average on net revenue per acre, holding all other variables constant are plotted in fig. 1.3. In summer, the relationship between "normal" temperatures and income per acre is such that there exists a threshold above which a unit increase in temperature leads to losses in profits. The value of this threshold is close to 31 degree C, implying that any temperature increase above that threshold are detrimental to farmers. It is noteworthy that the threshold value is almost identical at all quantiles, although a bit higher for farms with higher net profits per acre. Hence, these farmers may be less affected than farmers with low profits per acre by an increase in the average temperature. The same inverted-U shape relationship is observed with autumn precipitation, but the value of the threshold is around 25 degree C, and does not vary much across quantiles. Figure 1.3 shows that the average effect of an increase in summer temperature lowers profits per acre, and the magnitude of the average loss is amplified as well as its variability as ones moves up through the distribution of net revenues per acre. The impact of increasing temperatures in autumn mostly affects farms with high net revenues per acre.

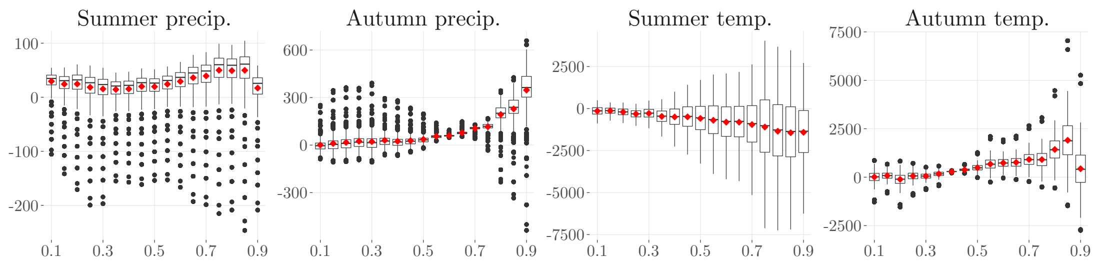
4.2 Other Variables

Besides climate variables, a few control variables are introduced in the model described by eq. (1.9): personal characteristics of the household, farm characteristics, geographic, and soil characteristics. They are briefly described in this section.



Notes: for summer and autumn, estimates for each quantile are represented by the solid black line ; 95% confidence intervals are shown by grey bands ; dashed and dotted lines are OLS estimates and associated 95% confidence intervals bounds, respectively.

FIGURE 1.2: Estimated Climate Parameters by Quantile for Net Revenues per Acre



Notes: The boxplots represent the variations of predicted yield at each quantile after a unit increase (one millimetre for precipitation and one degree Celsius for temperature) above the 30-year average, all other variables kept constant. Average change for each quantile is represented by a red rhombus.

FIGURE 1.3: Global Effects of a One Unit Rise in Climate Variables on Net Revenues per Acre for each Quantile Estimated

4.2.1 Personal Characteristics

Considering the OLS estimation only, the variations of the age of the head of the household plays a positive but not significant role in the explanation of the variations of net revenues. However, quantile regression coefficients show that up to the 70^{th} percentile, the older the head of the household, the lower net revenues per acre (fig. 1.4). However, for farms with higher net revenues per acre, the sign of the effects changes but becomes not significant at the 5% level. In addition to the age of the household, we add a second personal characteristics variable, literacy, which is defined here as the highest number of years of schooling within the members of the farm-household. This variable is included as a proxy for knowledge of agricultural techniques. If there

Notes: estimates for each quantile are represented by the solid black line ; 95% confidence intervals are shown by grey bands ; dashed and dotted lines are OLS estimates and associated 95% confidence intervals bounds, respectively.

FIGURE 1.4: Estimated Household Characteristics Parameters by Quantile for Net Revenues per Acre

were a pure location shift effect, the mean positive effect obtained with OLS regression reported in table 1.3 would be the same at each quantile. However, results from quantile regression show that net revenues per acre increase with years of schooling, although the effect is not significant for farms with low net revenues per acre, *i.e.*, for farms at the lower tail of the distribution.

4.2.2 Farm Characteristics

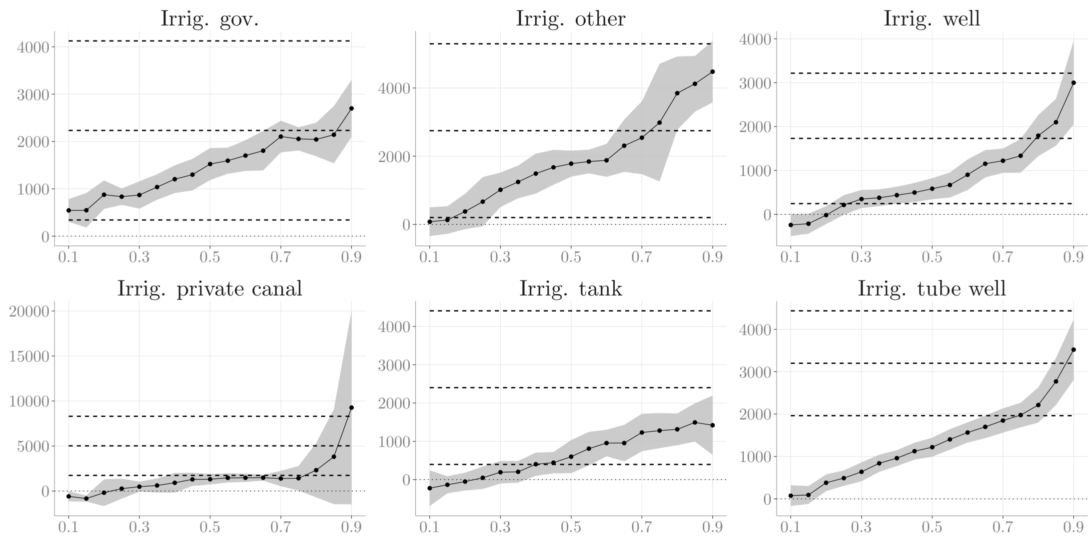
Bullock carts are introduced as a proxy for technology (Sanghi and Mendelsohn, 2008). The effect is found to be positive at each quantile, though only significant for a few quantiles for farms with the lowest net revenues per acre. The number of different cultures a farmer decides to grow is positive according to the least square estimate, but not significant. For farms at the upper tail of the distribution, above the 80^{th} percentile, the number of different cultures has indeed no significant effect on net revenues per acre. However, for farms with lower net revenues per acre, crop diversification is actually increasing profits.

For individuals with low to medium net revenues per acre, the global effect of an increase in workers per acre is positive though not significant at most quantiles. At the upper tail of the conditional net revenues per acre distribution, this effect becomes negative but remains not significant.

4.2.3 Irrigation

As previously discussed, the choice of irrigation is sensitive to climate. One way of addressing the question of irrigation in the Ricardian analysis is to introduce a variable related to the choice of irrigation, leaving aside any possible underlying endogenous bias.

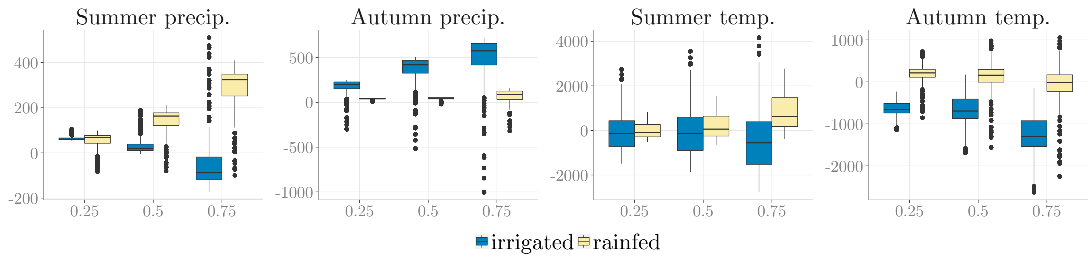
Not surprisingly, irrigating one's culture has a positive impact on net revenues per acre (table 1.3). Results from quantile regression show that farms at almost each quantile of the conditional net revenues per acre distribution actually realize benefits from using any irrigation technique rather than only rely on rainfall (fig. 1.5). In addition, the effect of irrigation on net revenues per acre grows as one moves up to the conditional distribution of net revenues per acre.



Notes: estimates for each quantile are represented by the solid black line ; 95% confidence intervals are shown by grey bands ; dashed and dotted lines are OLS estimates and associated 95% confidence intervals bounds, respectively.

Figure 1.5: Estimated Irigation Parameters by Quantile for Net Revenues per Acre

Instead of adding a variable linked to irrigation, some Ricardian studies choose to split the sample of farms in two categories; one for rainfed farms, and a second for irrigated ones. The first three columns of table 1.4 give the results of the estimation for rainfed farms at quantiles $\tau = \{0.25, 0.5, 0.75\}$. The last three columns give the results for irrigated farms. The shape of the relationship between net revenues per acre remains the same at each quantile both for rainfed and irrigated farms in all cases at the exception of the sensitivity to autumn temperatures for farms with the lowest net revenues per acre. The marginal effect of an increase of either temperature or precipitation from their 30-year average value is depicted in fig. 1.6. Irrigated and non-irrigated farms tend to positively respond to an increase in autumn precipitation though the magnitude of the effects on rainfed farms is less pronounced. An increase in summer temperature has mitigated effects. Farms at the lower tail of the net revenue per acre conditional distribution do not respond significantly to a unit increase in summer temperature. At the upper tail, however, irrigated farms tend to be negatively impacted by such an increase, while rainfed-only farms tend to be positively impacted by the unit increase of summer temperature. This may be explained by the fact that irrigated farms are already on locations where average temperature is higher than rainfed-only farms, so that an increase in summer temperature lowers profits by either reducing production or increasing production costs. The response of irrigated and rainfed-only farms to an increase in autumn temperature exhibit a more contrasted difference. For farms with low net revenues per acre, irrigated ones are negatively impacted while rainfed-only are positively impacted. At the opposite side of the distribution of net revenues per acre, we note that rainfed farms are not significantly sensible to autumn temperature variations, while irrigated farms exhibit a strong negative response to the increase in temperature.



Notes: The boxplots represent the variations of predicted yield at each quantile after a unit increase (one millimetre for precipitation and one degree Celsius for temperature) above the 30-year average, all other variables kept constant, for irrigated farms (in blue) and for rainfed farms (in yellow).

Figure 1.6: Global Effects of a One Unit Rise in Climate Variables on Net Revenues per Acre for each Quantile Estimated for Rainfed and Irrigated Farms Separately

5 Climate Scenarios

To give an idea of the potential consequences of climate change on Indian farmers' profits, we first envisage two climate scenarios and observe the changes in net revenues per acre under the new climate conditions. More scenarios are then considered and presented at the end of the section, by gradually altering precipitation and temperatures.

The scenarios exercises rely on the estimations made with all farms, irrigated or not. Net revenues per acre under historical climate conditions are predicted and then compared to predicted values under the new climate conditions given by the two scenarios.

To set up the scenarios, we follow Chaturvedi et al. (2012). The first one reflects a low concentration of greenhouse gas (roughly corresponding to the representative concentration pathway (RCP) 2.6, adopted by The Intergovernmental Panel on Climate Change for its fifth Assessment Reports in 2014), where average temperature for India is projected to globally increase by 1.7°C and total rainfall by 1.2%. It might be viewed as a mitigation scenario. The second scenario reflects high concentration of greenhouse gas (roughly corresponding to the RCP 8.5), mean temperature is projected to increase by 2.02°C and total rainfall by 2.4%. This scenario is more pessimistic than the first. As the model does not take CO_2 fertilization effects into consideration nor does it account for possible technological changes, the results displayed by the scenarios reported in table 1.5 and in figs. 1.7 and 1.8 might be biased, and should not be viewed as a forecasting exercise.

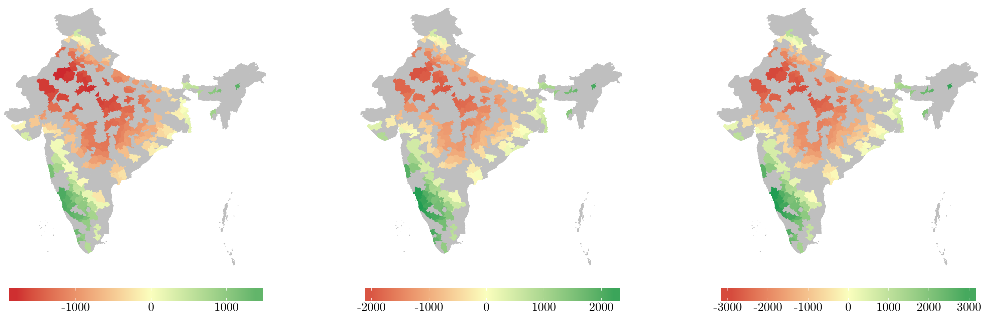
Under both scenarios, net revenues are on average negatively impacted by the increase in mean temperature and total rainfall. Farms with the lowest net revenues per acre (at the 25^{th} percentile of the distribution) experience a loss in net revenues per acre that amounts to a median of -736 Rupees per acre under the optimistic scenario, in which temperature increases by 1.7°C and precipitation by 1.2%. This corresponds to a median percent change of -37.7%.[10] Those losses grow higher at the upper part of the distribution of net revenues per acre, and reach a district median of -983 Rupees per acre. However, in terms of percent change, those losses are less important than those at the lower tail of the distribution, with a value of -18.5%. Under the second scenario, in which temperature and precipitation rise by 2.02°C and 2.4%, respectively, median losses in net revenues per acre are even higher than those observed under the more optimistic scenario. The median percent change in net revenues per acre decreases by -46% for farms with the lowest net revenues per acre and by 22.7% for farms with the highest net revenues per acre.

However, results given on a finer spatial resolution show some heterogeneity. As depicted in figs. 1.7 and 1.8, some districts are positively impacted by the changes operated on climate variables, while some other are getting worse. A distinction between

[10] We focus on the median percent change as some farms have net revenues per acre that are comprised between -1 and 1, leading to inflated percent changes.

north and south can be made, with most districts in the south experiencing gains in net revenues and districts in the north undergoing losses.

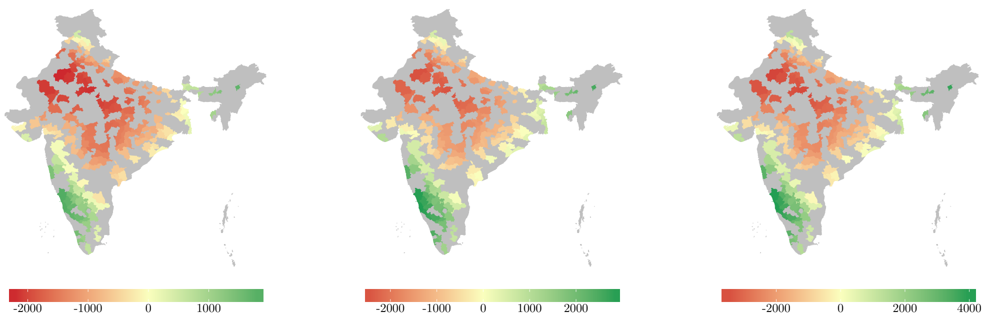
These findings are consistent with regional vulnerability to climate change found in O'Brien et al. (2004). Kumar and Parikh (2001) also found losses for northern states, but observed gains for eastern states. The few district for which observations are available in East India exhibit gains in net revenues per acre, but the number of district to represent East India is too small to generalize this result.



(a) $\tau = 0.25$ (b) $\tau = 0.5$ (c) $\tau = 0.75$

Notes: For a each quantile ($\tau = \{0.25, 0.5, 0.75\}$), the maps show the change in net revenues per acre under the first scenario, *i.e.*, following an increase in temperature of $1.7°$C and a 1.2% increase in total precipitation.

FIGURE 1.7: Average Change in Net Revenues per Acre by Districts and Quantiles Under Scenario 1 (Rupees per Acre)

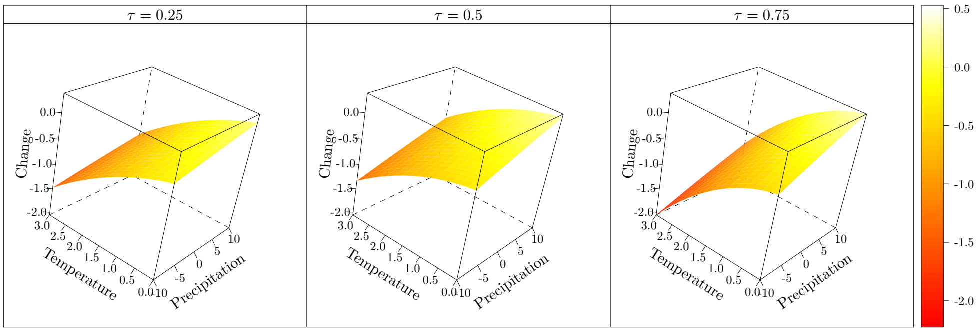


(a) $\tau = 0.25$ (b) $\tau = 0.5$ (c) $\tau = 0.75$

Notes: For each quantile ($\tau = \{0.25, 0.5, 0.75\}$), the maps show the change in net revenues per acre under the second scenario, *i.e.*, following an increase in temperature of $2.02°$C and a 2.4% increase in total precipitation.

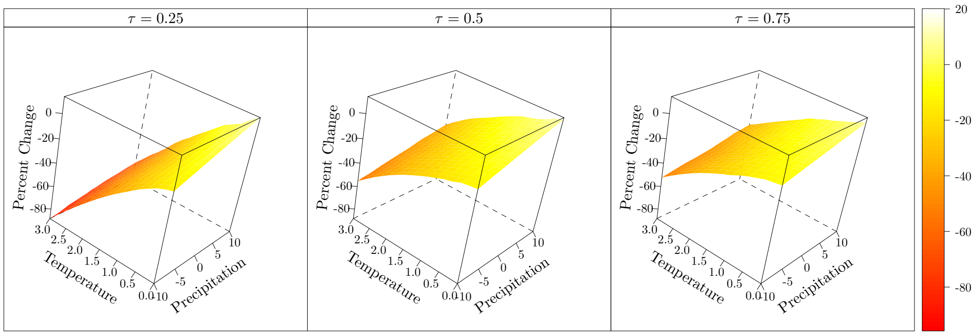
FIGURE 1.8: Average Changes in Net Revenues per Acre by Districts and Quantiles Under Scenario 2 (Ruppees per Acre)

To have a better insight of the possible effects of climate change on net revenues per acre of Indian farmers, we gradually increase 30-year average temperature from 0^{o}C to $+3^{o}$C in steps of 0.2^{o}C and we alter 30-year average total rainfall from -10% to $+10\%$ in steps of 1 percentage point. Thus, we consider 336 different scenarios. In each of them, the analysis previously done with the two climate scenarios is replicated, *i.e.*, predicting yields with historical climate conditions and comparing them to predicted yields under new climate conditions. Figure 1.9 plots the median change in net revenues at three different quantiles: $\tau = \{0.25, 0.5, 0.75\}$, and fig. 1.10 plots the same result expressed in percent deviation. It can be seen from the charts that temperature variation generates more variation in net revenues per acre than precipitation. Actually when precipitation increase, the losses generated by the variation in temperature are mitigated. Furthermore, we note that the situation of farms with high net revenues per acre is worsen more rapidly by an increasing temperature than that of farms with low net revenues per acre. However, if one looks at the change occurred in terms of percent deviations rather than in terms of magnitude, farms with the lowest net revenues per acre suffer from higher losses due to the increase in temperature.



Notes: For each quantile ($\tau = \{0.25, 0.5, 0.75\}$), the graphs show the median change in net revenues per acre following an increase in temperature (in Degree C) and a variation in total precipitation (percent change).

FIGURE 1.9: Median Changes in Net Revenues per Acre by District at Selected Quantiles (Thousand Rupees per Acre).



Notes: For each quantile ($\tau = \{0.25, 0.5, 0.75\}$), the graphs show the median percent change in net revenues per acre following an increase in temperature (in Degree C) and a variation in total precipitation (percent change).

FIGURE 1.10: Median Percent Changes in Net Revenues per Acre by District at Selected Quantiles (Thousand Rupees per Acre).

6 Concluding Remarks

This chapter presents an assessment of the effects of climate change on Indian agriculture. Agriculture represents a core part of the Indian economy and provides food and livelihood activities to much of the Indian population (more than 60% of its population is dependent on economic activities such as agriculture). India holds the second largest agricultural land in the world. According to different forecasts, emergent climate phenomena seem to be aggravating the agrarian distress in India. An estimated 70% of the country's arable land is prone to drought, 12% to floods, and 8% to cyclones. Expected changes in climate, especially rainfall, are also marked by significant regional variation, with the western and central parts witnessing a greater decrease in rainfall days compared to the other regions of the country (Kumar, 2011). The Fifth Assessment Report of the Intergovernmental Panel on Climate Change predicts that a temperature rise would result in a significant drop in Indian agricultural yield.

In India, previous studies on agriculture are mainly conducted on district-level aggregate data. In case of cross-sectional data, studies focus on specific regions which may lack generalization.

Our analysis, which is based on a representative sample of Indian farms, uses the Ricardian approach to examine the impact of climate change on Indian agriculture and describes farmers' behaviour to varying environmental factors. The study uses cross sectional data from the Indian Human Development Survey (IHDS). This survey is a nationally representative survey conducted between 2004 and 2005 on $41,554$ households across India. The empirical method involves the specification of the net revenues per acre as a function of climate variables and a set of economic variables. Empirical results show that climate variables have a significant impact on the farmers' net revenues per acre. Access to an irrigation scheme increases the net income per acre, *ceteris paribus*. Crop diversification too has a positive impact.

In addition, the chapter discusses the impact of climate scenarios on farmers' net revenues per acre. In general, the results indicate that increasing temperature as well as decreasing precipitation levels are damaging to Indian agriculture, both for small and large farms. Increasing precipitation, on the other hand, is beneficial to Indian profits, but when coupled with an increase in temperature, the negative effects of temperature dominate the positive effects of precipitation, leading to a global deterioration of Indian profits.

More research effort should be allocated into different points.

The empirical specification could be improved: although the analysis incorporates some farm characteristics, the role of technology, or the change in regional prices for the future, can be added. Another framework should therefore be considered, as the Ricardian analysis does not allow for an integration of such variables.

The second point is linked to the irrigation. Our analysis indicates that irrigation can and should play an important role in reducing the impacts of climate change on farmers. As India is one of the most water stressed countries in the world, the irrigation will be affected strongly by climate change (Edenhofer et al., 2014). We could enlarge the different climate scenarios by implementing different assumptions on the use of irrigation.

It would also be interesting to improve the analysis by studying the impact of climate change on food security in India. While the magnitude of impact of climate change looks to vary greatly by Indian region, climate change is expected to impact agricultural productivity.

Hence climate change may have an impact on food availability and therefore on food security. We can imagine that Indian agriculture cannot meet the objectives of food self-sufficiency[11] "*Given that about 250 million Indians lack food security, the challenge is to produce enough food "sustainably" to meet the increasing demand, despite shrinking resource availability*" (Swain, 2014). The analysis could be improved by trying to measure the impact on food supply at the country level.

The policy implications of our findings for climate change variability in Indian agriculture are important. These changes could affect water resource management, food security, and trade policy. Policy-makers will need to address adaptive measures to cope with changing agricultural patterns. Measures may include the introduction of the use of alternative crops, and promotion of water conservation and irrigation techniques to improve the access to water.

[11]This aspect could have impact on world commodities markets, one factor which explains unanticipated spike in international food prices in 2007-2008 was the growing demand of emerging countries such as India.

TABLE 1.3: Regression Results for Agricultural Net Revenues per Acre

	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	OLS
Intercept	−79555.80***	−94006.44***	−139151.08***	−11352.84
	(11780.86)	(15496.5)	(40924.14)	(103091.04)
		Climate variables		
Summer precip.	56.26	88.53**	134.29*	230.66
	(35.15)	(31.6)	(62.4)	(153.7)
Summer precip. sq.	−0.09	0.02	0.23	−1.43
	(0.44)	(0.39)	(0.76)	(1.63)
Autumn precip.	164.90***	266.29***	314.50***	958.84***
	(32.02)	(40.48)	(62.14)	(218.54)
Autumn precip. sq.	−2.57***	−4.64***	−7.16***	−16.78***
	(0.66)	(0.74)	(1.14)	(3.35)
Summer temp.	8290.82***	10400.53***	15832.46***	7921.68
	(1178.6)	(1232.13)	(2397.58)	(7631.02)
Summer temp. sq.	−133.31***	−165.84***	−250.89***	−116.62
	(18.65)	(19.99)	(38.69)	(123.4)
Autumn temp.	−3008.43***	−4219.36***	−5751.42**	−4887.96
	(757.94)	(728.55)	(1908.76)	(4472.84)
Autumn temp. sq.	59.64***	86.31***	114.45**	94.41
	(16.95)	(16.68)	(43.6)	(101.4)
		Personnal Characteristics		
Age of head of household	−3.30·	−2.93	−1.26	4.69
	(1.82)	(2.49)	(3.14)	(15.81)
Literacy	11.52**	29.17***	48.75***	82.41·
	(4.45)	(7.15)	(9.93)	(46.23)
		Farm characteristics		
No. bullock carts	141.96*	143.58·	34.87	−828.53
	(55.12)	(83.27)	(105.09)	(535.61)
No. different cultures	137.61***	156.40***	141.87***	118.02
	(17)	(27.57)	(34.67)	(164.96)
No. workers in the farm	51.02**	28.05	−42.44	235.98
	(18.12)	(28.15)	(37.08)	(177.66)
Irrig. gov.	834.27***	1523.57***	2055.05***	2233.45*
	(88.33)	(172.59)	(125.03)	(965.08)
Irrig. other	665.82·	1781.31***	2984.87***	2748.29*
	(367.51)	(194.84)	(880.65)	(1299.56)
Irrig. well	214.08·	584.27***	1334.50***	1730.98*
	(114.03)	(122.96)	(196.01)	(758.18)
Irrig. private canal	261.93	1307.39***	1422.10*	5017.65**
	(567.82)	(298)	(694.56)	(1674.99)
Irrig. tank	47.82	599.21**	1279.54***	2401.81*
	(149.62)	(220.3)	(233.84)	(1023.04)
Irrig. tube well	488.63***	1218.72***	1976.77***	3199.56***
	(93.21)	(114.21)	(147.64)	(630.85)
		Geographic and Soil Characteristics Variables		
Latitude	53.19	48.96	−166.10·	108.40
	(48.9)	(56.94)	(88.04)	(368.6)
Longitude	−176.55***	−276.99***	−425.67***	−733.57**
	(26.02)	(34.23)	(54.26)	(235.73)
Pop. density	−0.18	−0.02	0.42	2.03
	(0.17)	(0.23)	(0.46)	(1.28)
Gravel Content	5.25	−19.76	−57.32*	86.52
	(14.63)	(19.95)	(24.78)	(122.92)
Sand Fraction	−32.93**	−30.10·	−60.45	−192.89·
	(10.85)	(17.34)	(51.46)	(100.13)
Silt Fraction	52.27***	43.78*	11.35	−211.38·
	(11.59)	(20.74)	(54.11)	(126.31)
Clay Fraction	−49.87***	−62.16**	−130.14*	−208.25·
	(13.79)	(20.34)	(52.97)	(117.11)
pH (H2O)	−2.44	324.42	570.97·	609.89
	(128.43)	(198.37)	(313.95)	(1181.85)
Calcium Carbonate	−79.68***	−142.96***	−227.29***	−192.67
	(21.23)	(37.38)	(56.87)	(239.66)
Sodicity	83.30**	142.63***	152.60***	236.96
	(27.05)	(33.06)	(41.2)	(191.75)
No Observations		7751		

Notes: Dot (·), asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10%, 5%, 1% and 0.1%, respectively. Standard errors are in parentheses below the parameter estimates.

Table 1.4: Regression Results with Only Rainfed or Irrigated Farms

	Rainfed-Only			Irrigated		
	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$
Intercept	-44046.09^{**}	-71852.06^{***}	-103000.17^{*}	-211074.32^{***}	-261875.32^{***}	-294728.72^{***}
	(15988.14)	(18464.39)	(47097.59)	(29302.4)	(31884.44)	(87114.37)
Climate variables						
Summer precip.	120.97^{**}	247.75^{***}	471.22^{***}	48.59	-28.99	-256.98^{*}
	(43.38)	(40.37)	(80.5)	(59.5)	(59.47)	(100.38)
Summer precip. sq.	-1.23^{*}	-1.99^{***}	-3.46^{***}	0.34	$1.32^{\cdot}$	4.65^{***}
	(0.53)	(0.46)	(0.94)	(0.68)	(0.74)	(1.36)
Autumn precip.	50.15	62.46	$185.21^{\cdot}$	275.89^{***}	557.30^{***}	807.15^{***}
	(56.13)	(39.5)	(105.13)	(68.09)	(63.35)	(105.88)
Autumn precip. sq.	-0.33	-0.62	$-3.83^{\cdot}$	-4.38^{***}	-8.16^{***}	-13.75^{***}
	(1.18)	(0.7)	(1.98)	(1.18)	(1.08)	(2.21)
Summer temp.	4837.10^{**}	8010.25^{***}	12163.52^{***}	17061.88^{***}	21953.13^{***}	27674.19^{***}
	(1544.32)	(1663.46)	(3595.83)	(2513.09)	(2512.56)	(5331.02)
Summer temp. sq.	-78.95^{**}	-127.25^{***}	-184.64^{**}	-272.97^{***}	-350.60^{***}	-447.97^{***}
	(24.69)	(26.52)	(57.46)	(40.37)	(40.54)	(85.36)
Autumn temp.	-2594.36^{**}	-4356.22^{***}	-5887.76^{*}	$-2343.16^{\cdot}$	-4147.26^{***}	-5878.41
	(958.37)	(932.72)	(2337.52)	(1417.33)	(1138.76)	(3757.81)
Autumn temp. sq.	58.33^{**}	93.78^{***}	122.06^{*}	37.16	75.98^{**}	100.64
	(21.11)	(20.59)	(51)	(32.89)	(26.32)	(86.55)
Personnal Characteristics						
Age of head of HH	-3.12	-2.90	6.26	-4.87	-2.68	-4.53
	(2.46)	(2.36)	(5.1)	(3.49)	(3.42)	(4.61)
Literacy	22.26^{**}	35.10^{***}	53.52^{***}	0.20	22.14^{*}	54.24^{***}
	(7.11)	(6.45)	(15.08)	(10.6)	(10.07)	(13.43)
Farm characteristics						
No. bullock carts	27.22	116.09	270.73	146.38	13.45	-322.12^{**}
	(103.19)	(97.99)	(249.58)	(123.27)	(122.61)	(117.4)
No. different cultures	109.43^{***}	111.84^{***}	55.36	149.21^{***}	189.84^{***}	168.40^{***}
	(29.39)	(29.48)	(55.09)	(30.21)	(32.34)	(46.73)
No. workers in the farm	$58.32^{\cdot}$	103.67^{***}	12.75	32.35	-20.53	-75.25
	(29.91)	(31.15)	(63.01)	(36.19)	(37.41)	(59.49)
Geographic and Soil Characteristics Variables						
Latitude	146.30^{*}	188.49^{*}	$215.74^{\cdot}$	-62.01	-79.26	-559.51^{***}
	(73.88)	(75.05)	(126.49)	(100.79)	(97.8)	(150.65)
Longitude	-69.07	-119.23^{**}	-412.93^{***}	-243.25^{***}	-447.77^{***}	-626.04^{***}
	(42.46)	(43.07)	(92.92)	(52.58)	(47.02)	(91.04)
Pop. density	-0.15	-0.37	-1.33^{*}	-0.05	-0.07	0.76
	(0.3)	(0.4)	(0.66)	(0.33)	(0.29)	(0.6)
Gravel Content	-11.76	-95.77^{***}	-152.30^{***}	76.75^{*}	35.75	-45.24
	(22.02)	(26.42)	(37.76)	(31.32)	(33.39)	(43)
Sand Fraction	-10.53	$-30.49^{\cdot}$	-117.49^{*}	-32.71	91.11^{**}	138.60^{*}
	(14.28)	(17.74)	(57.27)	(30.29)	(33.18)	(58.92)
Silt Fraction	48.22^{*}	81.61^{***}	65.54	33.60	138.82^{***}	159.05^{**}
	(20.52)	(23.74)	(63.28)	(34.79)	(37.81)	(61.44)
Clay Fraction	-24.78	-76.24^{***}	-245.24^{***}	-40.39	74.55^{*}	74.59
	(18.18)	(20.46)	(64.23)	(35.15)	(35.86)	(74.27)
pH (H2O)	-172.72	213.22	1493.75^{**}	-400.78	-459.19	-84.63
	(229.09)	(216.25)	(499.67)	(350.93)	(348.4)	(645.43)
Calcium Carbonate	-9.56	-181.83^{**}	-584.89^{***}	23.95	7.16	-79.45
	(51.65)	(57.04)	(112.69)	(56.36)	(60.56)	(99.51)
Sodicity	50.20	83.65	87.57	73.98	183.63^{***}	134.25^{*}
	(52.76)	(64.03)	(118.83)	(45.56)	(41.68)	(54.87)
No Observations	4643	4643	4643	3095	3095	3095

Notes: The estimations for rainfed-only farms at three different quantiles ($\tau = \{0.25, 0.5, 0.75\}$) are provided in the first three columns, and the estimations for irrigated-only farms on the last three columns. Dot (·), asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10%, 5%, 1% and 0.1%, respectively. Standard errors are in parentheses below the parameter estimates.

TABLE 1.5: Changes in Net Revenues per Acre by Districts at Each Quantile (Rupees)

Scenario	τ	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std Dev.	Median % Change
Temp $+1.7°$C Precip. $+1.2\%$	0.25	-1837	-1213	-736	-536	-39.3	1569	896	-37.7
	0.50	-2029	-1234	-599	-364	332.4	2383	1161	-18.8
	0.75	-3049	-1875	-983	-595	347.0	3404	1690	-18.5
Temp $+2.02°$C Precip. $+2.4\%$	0.25	-2220	-1471	-907	-667	-66.9	1852	1066	-46.0
	0.50	-2447	-1487	-732	-454	379.7	2856	1382	-23.0
	0.75	-3691	-2286	-1222	-760	373.8	4071	2010	-22.7

Notes: This tables reports changes in net revenues per acre under both climate scenarios at different quantiles ($\tau = \{0.25, 0.5, 0.75\}$), relative to predicted net revenues per acre under historical climate conditions.

Chapter 2

Climate Change and Food Security: a Farm-Household Model

Joint work with Catherine Benjamin (University of Rennes 1)

1 Introduction

A notable achievement of the climate change research community is that climate change is now defined as a major topic on the political agenda. Thus, the last 2015 Paris international climate agreement marks the greatest collective effort the world has ever seen to tackle the climate crisis.[1] On that occasion, 175 parties (developed and developing) have agreed to limit their emissions to relatively safe levels, of $2°C$ with an aspiration of $1.5°C$, with regular reviews to ensure these commitments can be increased in line with scientific advice. In addition, financial aid will be provided to poor nations to help them cut emissions and cope with the effects of extreme weather. This agreement was possible thanks to the results of numerous studies which provide compelling evidence of climate change. Work undertaken by an United Nations body, the Intergovernmental Panel on Climate Change (IPCC), have produced key information on the possible damages of climate change on biological and human systems. Many elements have been identified in recent years (Edenhofer et al., 2014). Of the

[1] https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf

various aspects related to climate change, the possible increase in climate variability has been recognized as one of the most critical issues.

Climate variability refers to the climatic parameters of a country or a region varying from its long-term mean. Recent IPPC report predicts that increasing frequencies of heat stress, drought and flooding events are projected for the end of this century and these events are to have many adverse effects over and above the impacts due to changes in mean variables alone (Edenhofer et al., 2014). Changes in the frequency and severity of extreme climate events and in the variability of weather patterns will have significant consequences for human and natural systems.

Particular attention has been devoted to agricultural effects of climate change. Climate is the primary determinant of agricultural productivity; climatic variables (level of precipitation, temperature) define key inputs in the production process. This has motivated a number of economic assessments of the potential effects of long-term climate change on agriculture. This body of research addresses possible physical effects of climate change on agriculture, such as changes in crop and livestock yields (Chen et al., 2004; McCarl et al., 2008; Schlenker and Roberts, 2009), as well as the economic consequences of these potential yield changes for instance the effects on farm income (Sanghi and Mendelsohn, 2008), potential changes in patterns of food production and prices (Miao et al., 2015).

Climate change affects food production and agriculture and in many ways.

First, it has a direct effect on the performance on agriculture through the impact on crop yields. This is particularly true for rural farmers in developing countries where agricultural production is highly dependent on rainfall and sensitive to the weather. Land use, and changes in agricultural productivity linked to climatic variability have been studied widely in developing countries (Khanal et al., 2014).

The general consensus of these studies is that changes in temperature and precipitation will result in changes in land and water regimes that will subsequently affect agricultural productivity. Research has also shown that specifically in tropical regions, with many of the poorest countries, impacts on agricultural productivity are expected to be particularly harmful (Mendelsohn, 2008). In addition, experts predict tropical regions will see both a reduction in agricultural yields and a rise in poverty levels.

Secondly, climate change has indirect effects by affecting growth and distribution of incomes, demand for agricultural products and thus affects different dimensions of food security (Schmidhuber and Tubiello, 2007). Changes in climatic conditions have already affected the production of some staple crops in some very poor countries, and future predicted climate change threatens to exacerbate this. Given that agriculture is highly sensitive to climate patterns, changes in temperature and rainfall can reduce agricultural output. For the most vulnerable people, lower agricultural output would also mean lower income. Mendelsohn et al. (2007) also showed that historically, climate is highly correlated to agricultural incomes. Under climate change, increased temperatures and erratic precipitation are likely to result in higher rural poverty, and lower rural income for food. Under these conditions, the poorest people – who already use most of their income on food – would have to sacrifice additional income to meet their nutritional requirements. Furthermore, the magnitude of the projected impacts of climate change suggests that it is reasonable to expect that changes in production will be large enough to drive an increase in agricultural prices in some regions. At last, commodity price volatility is likely to intensify and become more widespread due to climate change.

A consensus shared by different studies is that the negative impacts of climate change are more severely felt by poor people and poor countries. Developing countries, particularly the least developed ones, look to be more vulnerable because of their high dependence on natural resources, and their limited capacity to cope with climate variability and extreme climatic events. Furthermore, although declining, the value added of agriculture in these countries' GDP remains high, and and a large part of the population is still directly or indirectly dependent on agriculture.

Among the most significant impacts of climate change is the potential increase of food insecurity and malnutrition. Numerous studies show the possibility of increased food insecurity from climate change (see, *e.g.*, Butt et al., 2005; Deaton, 1997).

There is still an extensive debate on how climate change will affect world food consumption (Howard et al., 2014).

This chapter contributes to the literature in two ways. First the effects of climate change on both production and consumption decisions are investigated in a large sample of Indian rural households. In developing countries, farm households are often both producers and consumers of food. The impact of a price increase in any main agricultural product goes beyond the usual income and substitution effects of basic microeconomics. A cursory look at the model of the agricultural household shows that price changes of basic food items has winners and losers (Singh et al., 1986). In case of a price increase, the winners are those farmers who are net-sellers of the crop and who have enough resources in terms of land, labour and other inputs to benefit from the price increase. The losers are the net-buyers of the crop. The latter are land-poor farmers.

Secondly most studies have focused on the food security issue at the national level which may mask food insecurity at the household level. For a better understanding of farm household food security status, it is preferable to use methods and tools working at micro-level, which allows to provide detailed results on a farm household scale and to capture heterogeneity across households.

The remainder of this second chapter is organized as follows. Section 2 describes the conceptual framework to motivate the effects of climate change both on production and consumption behaviour. Section 3 presents the empirical strategy retained in the analysis. Section 4 introduces the data. Section 5 focuses on estimation results. Finally, section 6 concludes.

2 A Farm Household Modelling

The mixture of the economics of the firm and of the household is the main feature of most agricultural families in developing countries and provides the starting point for our analysis.

Most people in developing countries often consume at least a portion of the output of their productive activities. As noted by De Janvry et al. (1991) farm household in underdeveloped countries are usually located in an environment characterized by a number of market failures for some of its products (*e.g.*, some foods, particularly the most perishable or bulky) and for some of its factors (*e.g.*, child labour or family labour with low access to the labour market). An extreme case of market failure is simply the non-existence of a market, for example, due to cost transactions (missing means of transportation) and so households do not in participate in markets. In that particular case implicit food prices appear which means that food prices are endogenous and are dependent on household preferences. The household faces wide price bands, implicit prices levels are between the low price at which the household could sell a commodity and the high price at which household could buy that product. Faced with this wide price band, the household may be better off choosing self-sufficiency in that good if its subjective price (defined as the price which equates its supply and demand) falls inside the band.

At the same time, the sale of crops produced on the family farm is an important income source for the farm household. Consequently, individuals make simultaneous decisions about production (the level of output, the demand for factors, and the choice of technology) and consumption (labour supply and commodity demand).

Building on traditional farm household models (see Singh et al., 1986), we consider a farm household whose objective is to maximise utility, subject to different positivity constraints.

The household's problem can be represented as follows:

$$\max_{C, C_L, L^H, L^F, H^O} \mathcal{U}(C, C_L; Z^H) \tag{2.1}$$

$$\text{s.t.} \quad p \cdot \left(q\left(L^F + L^H; Z^A, W\right) - C\right) - wL^H + w_O L^O \geq 0 \tag{2.2}$$

$$C_L + L^F + L^O = T, \tag{2.3}$$

where $\mathcal{U}(\cdot)$ defines the household's utility function, C is total household own consumption, C_L is leisure, Z^H defines a vector household characteristics (number of dependants, gender and age of the head of the household, ...), p is the output price, q is the quantity produced, L^F is the amount of on-farm family labour, L^H is the amount of on-farm hired labour, w the cost of hired labour, w^O off farm wage, Z^A are the vector of quasi fixed factors of production (*e.g.*, cultivated surface), W a vector of exogenous variables which could affect farm production (such as climate variables), L^O is the amount of off-farm family labour, and T is total time available.

Following Henning and Henningsen (2007), we consider four different labour regimes. The first regime concerns households in which members provide work outside the family plot and hire non-family labour to work on the family plot. The second regime applies to households that provide work outside the family plot and do not hire any labour. The third regime includes households that do not provide work outside the family plot and hire non-family labour to work on their farm. The fourth and last regime is for households that neither work off-farm nor hire non-family labour.

3 Empirical Strategy

This section first presents the empirical methodology used to estimate the production function of the farm-households. Details on the estimation of the shadow wage of family work on the farm are then provided. These shadow wages are then used in the consumption decision model, as a valuation of the opportunity cost of labour.

3.1 The Production Function

The form of the agricultural production function used in this analysis is a standard Cobb-Douglas:

$$\ln Y_{A,n} = \alpha_0 + \sum_{j=1}^{J} \alpha_{1,j} X_j + \sum_{c=1}^{C} \alpha_{2,c} W_c + \sum_{k=1}^{K} \alpha_{3,k} Z_k + \varepsilon_{Y_a,n}, \quad \forall n = 1, \ldots, N, \tag{2.4}$$

where $Y_{A,n}$ is the total agricultural output value of the n^{th} household, $X_j; j \in \{1, \ldots, J\}$ indicates the j^{th} input (hours spent on farm by household members, hours spent on farm by hired people, cultivated area), $W_c; c \in \{1, \ldots, C\}$ refers to the c^{th} climate variable (temperature and rainfall, both expressed as their 30-year average value) that include squared terms to account for non-linear effects of climate on production, and $Z_k; k \in \{1, \ldots, K\}$ is the k^{th} control variable. Control variables include farm-household characteristics (mean age and gender of the head of the household), location-specific variables (distance of the farm-household from the nearest town, distance from the nearest public distribution system (PDS), distance from the nearest Pucca road,[2] percentage of households with electricity within the village, state in which the household is located, and soil characteristics). The parameters α_1, α_2, and α_3, as well as the constant α_0, are parameters to be estimated, and ε_{Y_a} is a standard error term with zero mean and variance $\sigma^2_{Y_a}$.

The production function is first estimated by ordinary least square (OLS). Then, to account for the endogeneity of household labour on farm, we proceed to an instrumental variable (IV) estimation, using household specific variables (number of working-age members, number of children) and market prices of most important goods (pure market goods, price of crops and price of animal products) as instruments. We finally estimate the production function in a two-step procedure to correct for selectivity-bias that occurs because agricultural output is observed only if the household participates in the agricultural market, either by providing family labour, employing labour, or both. Thus, a two-step Heckman procedure is used (Heckman, 1979). The first step

[2] There are two types of roads in India, Kutcha and Pucca roads, the latter being of better quality than the former.

consists in estimating the factors affecting the decision on whether or not to participate in the agricultural market, by means of a probit model. The identification variables of this first step are the number of dependants, *i.e.*, children and teenager younger than 15 or seniors older than 60, and number of working-age household members, *i.e.*, between 15 and 60. The second step consists in estimating the production function for the selected individuals that participate in the agricultural market, using an IV approach, with the same instruments mentioned previously.

3.2 The Shadow Wage

Farm household's working age members may choose to work on or off the family plot. If they decide to work off the family farm, it is possible to observe the wage they receive from their activities. However, when they work on the household farm, some assumptions need to be made to estimate the value of their work. As stated by Castagnini et al. (2004), if one assumes perfectly competitive markets, household members are indifferent between working on or off the family plot, at the market equilibrium. However, the underlying assumption of separability may be questioned in case of market failures, especially in developing countries. The labour supply choices of each individual in a family might not be separable from the labour needs of the household farm (Skoufias, 1994). In such cases, the common methodology is to estimate a shadow price of labour (see *e.g.*, Jacoby, 1993; Sicular and Zhao, 2004). This shadow price P_L is obtained by assuming that household farm work is remunerated at its marginal productivity, and can thus be calculated as:

$$P_L = \frac{\hat{\alpha}_{1,L_F} Y_A}{L_F}, \tag{2.5}$$

where $\hat{\alpha}_{1,L_F}$ is the estimated coefficient associated with family hours of work on farm from eq. (2.4), Y_A is agricultural output and L_F is the amount of family hours on the household plot.

3.3 The Consumption Decisions

We follow Henning and Henningsen (2007) to model the consumption decisions of farm households, using an Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980) framework. Each household can consume four different goods: pure-market goods m, cereals c that can be either self-produced or bought on the market, animals or animal-derived products a, and leisure L. Pure-market goods are an aggregation of sugar, kerosene and oil; cereals are composed of rice, wheat, pulses, gur and other cereals; animal goods are composed of milk, meat, chicken, fish, and eggs. The prices associated with pure-market goods, cereals and animal-derived products are weighted means of observed prices of each commodity used to define each of the three categories of goods, where the weights are defined as the share of each commodity in the annual consumption of the household. The price of leisure is the shadow wage of eq. (2.5), *i.e.*, the opportunity cost of not working. The number of hours dedicated to leisure is obtained by first computing total available time for the household. We assume that family members aged between 15 and 60 has 10 hours a day available for work, while members older than 60 can only devote a maximum of 5 hours a day to work. Family members then allocate their available time between work (on-farm and off-farm) and leisure. Hence, the amount of leisure time is calculated by deducting the number of declared hours worked to the total available time.

The demand functions of the AIDS are the expenditure shares of each of the four goods $i \in \{m, c, a, L\}$ at the household level:

$$w_{in} = \beta_i + \sum_{j \in \{m,c,a,L\}} \gamma_{ij} \ln P_{jn} + \delta_i \ln \frac{Y_n}{\mathcal{P}_n} + \sum_c \zeta_{ic} W_{cn} + \varepsilon_{w_i,n}, \tag{2.6}$$

$$\text{s.t.} \sum_{i \in \{m,c,a,L\}} \beta_i = 1 \quad \text{(adding-up)}, \tag{2.7}$$

$$\sum_{i \in \{m,c,a,L\}} \delta_i = 0 \quad \text{(adding-up)}, \tag{2.8}$$

$$\sum_{j \in \{m,c,a,L\}} \gamma_{ij} = 0 \quad \text{(homogeneity in prices)}, \tag{2.9}$$

$$\gamma_{ij} = \gamma_{ji}, \forall i, j \in \{m, c, a, L\} \quad \text{(symmetry)}, \tag{2.10}$$

$$\text{where} \ln \mathcal{P}_n = \beta_0 + \sum_{i \in \{m,c,a,L\}} \beta_i \ln P_{in} + \frac{1}{2} \sum_{i \in \{m,c,a,L\}} \sum_{j \in \{m,c,a,L\}} \gamma_{ij} \ln P_{in} \ln P_{jn}, \tag{2.11}$$

where $w_{in} = \frac{P_{in}C_{in}}{Y_n}; i \in \{m, c, a, L\}$ represents the expenditure share of the i^{th} type of good of the n^{th} household, $P_{in}; i \in \{m, c, a, L\}$ is the consumer prices, Y_n the full income, $\mathcal{P}_n$ is the translog consumer price index, and W_c represents the c^{th} shifter variable (*i.e.*, climate). The parameters β_i, γ_{ij}, δ_i, and ζ_{ic} are unknown parameters. They are estimated using an iterative linear least squares method by the `R` add-on package "micEconAids" (Henningsen, 2014).[3]

The consumption decisions are examined for all rural households that produce cereals, and also for the different subsets based on the participation in the labour market described in section 2. We calculate price and income elasticities for each subset.

The income elasticity measures how much the demand for a good is affected by the changes in income. It is calculated as:

$$e_i = \frac{\partial q_i}{\partial Y} \frac{Y}{q_i}, \tag{2.12}$$

where e_i is the income elasticity of good i, q_i the demanded quantity of that good, and Y represents total income.

The price-elasticity of demand measures the percent change in quantity demanded for a good i with respect to an increase in the price of a good j:

$$\epsilon_{ij} = \frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i}, \quad \forall i, j \in \{m, c, a, L\}, \tag{2.13}$$

where p_j is the price of good j.

The eq. (2.6) can be viewed as a Marshallian demand function in budget shares. It is possible to derive the Marshallian price elasticities of good i with respect to good j as follows:

$$\epsilon_{ij}^{M} = -\mathbb{1}_{i=j} + \frac{1}{w_i} \left[\gamma_{ij} - \delta_i \left(w_j - \delta_j \ln \frac{Y}{\mathcal{P}} \right) \right], \quad \forall i, j \in \{m, c, a, L\}, \tag{2.14}$$

where $\mathbb{1}_{i=j}$ is the indicator function that takes the value 1 when $i = j$ and 0 otherwise.

In the presence of shifter variables, which is the case in our analysis, the coefficients δ_i must be adjusted as follows:

$$\delta_i^* = \delta_i + \sum_{j=1}^{m} \zeta_{ij} W_j, \quad \forall i \in \{m, c, a, L\}. \tag{2.15}$$

[3]The leisure demand equation is dropped from the system to avoid singularity problems. The parameters β_i, γ_{ij} and δ_i for this equation are obtained using the adding-up properties.

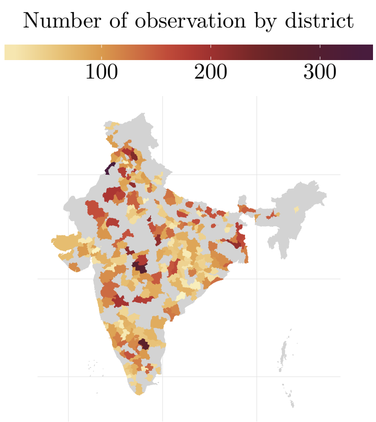
From these Marshallian elasticities, it is possible to derive the compensated elasticities, or Hicksian elasticities through the Slutsky equation:

$$\epsilon_{ij}^{H} = \epsilon_{ij}^{M} + w_j \times e_i, \quad \forall i, j \in \{m, c, a, L\}. \tag{2.16}$$

4 Data

This study uses a nationally representative multi-topic survey of households across India, the Indian Human Development Survey 2 (Desai and Vanneman, 2016). It was conducted between 2011 and 2012 in $42,152$ households, and provides rich information regarding consumption expenditures. Locations for each household can be traced at the district level and is not provided at a finer geographical level for anonymity purposes.

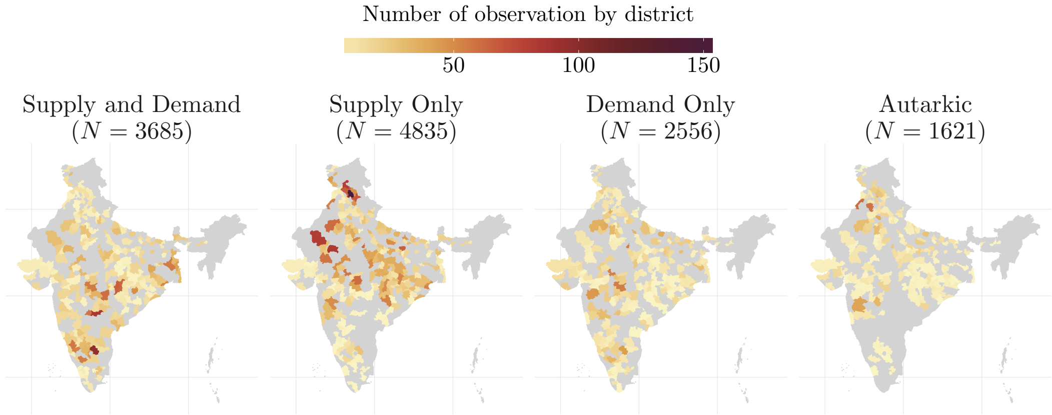
We only focus on rural households. The final sample covers a wide geographical surface, as depicted in fig. 2.1, where the number of observation is represented. In total, the final sample used in this study is composed of $22,892$ households from 258 districts in 23 states. The minimum number of observation within each state ranges from 12 (Dadra and Nagar Haveli) to $2,501$ (Uttar Pradesh).



Note: The map shows the geographical distribution of the 22, 892 rural households from the national representative survey, at the district level.

Figure 2.1: Number of Observations per District

As we are interested in studying the production and consumption decisions on farm-households, we divide the sample into two categories of rural households: agricultural and non agricultural. The former is composed of $12,206$ households while the latter contains $10,686$ households that produce crops. Households that produce crops are further divided into the four labour regimes previously described in section 3.1. As shown in fig. 2.2, all categories cover a similar and large surface of India.



Notes: The maps show the geographical distribution of farm-households from the national representative survey, apportioned according to the different labour regimes: "Supply and Demand", for households that both engage in off-farm work and hire labour on their family plot; "Supply only", for households that engage in off-farm work and do not hire any labour on their family plot; "Demand only", for households that not engage in off-farm work and hire labour on their family plot; and "Autarkic", for households that neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.2: Number of Observations per District and Labour Regime

The remainder of this section describes in more details the composition of the sample data. The descriptive statistics of the different variables are reported in table 2.1, where households are regrouped according to their labour regime.

4.1 Labour, Income, and Farm Characteristics

Working-age members of the family can allocate their time between work, either in or off the farm plot, and leisure. On average, farm-households have an endowment of $12,872.54$ hours, $1,663.33$ of which (13%) devoted to on-farm work, $1,397.23$ (11%) to off-farm work, and $9,811.98$ (76%) to leisure.

The average net annual per capita income of farm-households is $22,599$ Rupees. However, it can vary by a factor of almost two according to the labour regime. In fact, households that do not hire labour and also engage in off-farm work (Supply Only) have an average net per capita income of $16,0168$ Rupees only, while autarkic and households that hire labour to work on their farm and do not engage in off-farm work (Demand Only) receive twice as much a year. There is also some regional heterogeneity, as depicted in fig. 2.3. The map shows that the average net per capita incomes vary from $10,735$ Rupees (Odisha) to $62,998$ Rupees (Punjab), while the map on the right shows that agricultural per capita net income varies from -613 Rupees (Daman

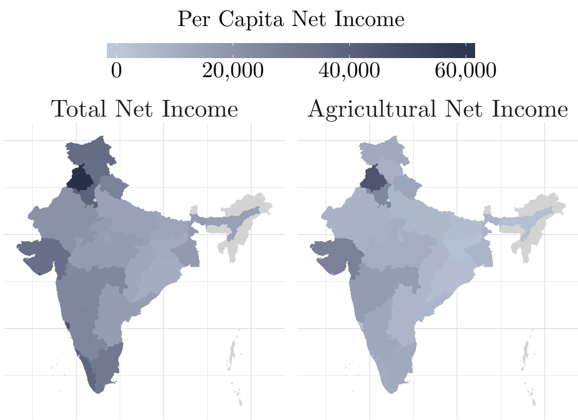
Table 2.1: Descriptive Statistics According to the Different Labour Regimes

	Not Ag.	All Ag.	Supply and Demand	Supply Only	Demand Only	Autarkic
Household Characteristics						
No. Persons (Persons)	4.39	5.43	5.38	5.55	5.28	5.39
No. Children (0-14) (Persons)	1.38	1.62	1.52	1.78	1.48	1.60
No. Teens (15-20) (Persons)	0.51	0.67	0.63	0.74	0.58	0.71
No. Adults (21-60) (Persons)	2.04	2.54	2.66	2.53	2.46	2.40
No. Seniors (60+) (Persons)	0.47	0.59	0.57	0.49	0.76	0.68
No. Working Age (15-60) (Persons)	2.55	3.21	3.29	3.27	3.04	3.10
No. Dependents (<15 U >60) (Persons)	1.85	2.22	2.09	2.27	2.24	2.28
Mean Age in the HH (Years)	39.43	39.34	39.28	37.72	41.94	40.31
Labour						
Total Available Time (Hours)	10,203.45	12,872.54	13,121.14	12,946.72	12,527.17	12,644.47
On-farm HH Labour (Hours)	0.00	1,663.33	1,588.68	1,407.24	2,074.00	1,952.57
Off-farm HH Labour (Hours)	2,335.48	1,397.23	2,079.74	2,094.45	0.00	0.00
On-farm Hired Labour (Hours)	9.53	322.72	454.45	0.00	969.47	0.00
On-farm Labour (Hours)	9.53	1,986.05	2,043.12	1,407.24	3,043.47	1,952.57
Leisure (Hours)	7,867.96	9,811.98	9,452.73	9,445.03	10,453.17	10,691.90
Income						
Net Income (INR)	80,766.84	112,558.72	111,821.78	82,871.03	148,613.43	146,666.35
Net Income per Cap. (INR /Cap.)	19,897.11	22,599.24	22,270.44	16,168.41	30,936.11	29,545.71
Net Ag. Income (INR)	4,278.03	56,620.08	43,290.97	26,583.78	103,829.30	101,919.13
Net Ag. Income per Cap. (INR /Cap.)	1,172.25	11,278.13	8,528.62	5,161.15	21,368.14	19,849.54
Farm Characteristics						
Crops Output (INR)	-	4,568.68	4,020.32	2,564.06	7,771.33	6,773.32
Cultivated Area (Acre)	-	4.98	4.47	2.76	8.83	6.72
Crops Kept (%)	-	87.75	83.89	90.73	85.72	90.44
Dist. to Nearest Town (km)	-	14.07	14.06	14.96	13.20	12.76
Dist to Nearest PDS (km)	0.32	0.58	0.46	0.74	0.47	0.56
Weather						
Rainfall (30-year average, mm)	2.89	2.70	2.94	2.61	2.71	2.41
Temp. (30-year average, Deg. C)	25.61	25.29	25.86	24.92	25.57	24.72
Soil Characteristics						
Gravel Content (%vol.)	8.53	8.63	8.65	8.90	8.29	8.35
Sand Fraction (%wt.)	40.19	40.84	40.06	42.23	39.26	40.84
Silt Fraction (%wt.)	31.24	30.68	30.11	30.42	31.26	31.84
Clay Fraction (%wt.)	28.16	27.96	29.43	26.66	29.22	26.73
No. obs.	10,686.00	12,206.00	3,452.00	4,715.00	2,445.00	1,594.00
% of Agricultural Households	-	100%	13.1%	20%	28.3%	38.6%

Notes: Households of the sample are either "Not Ag." if they do not engage in the agricultural sector or "All Ag." if they do. All agricultural households are furthermore divided into four categories according to their participation in the job market. These four categories are as follows: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

and Diu) to $45,800$ Rupees (Punjab). Both maps exhibit a distinction between West and East India, with lower incomes in east India than in the West part of the country.

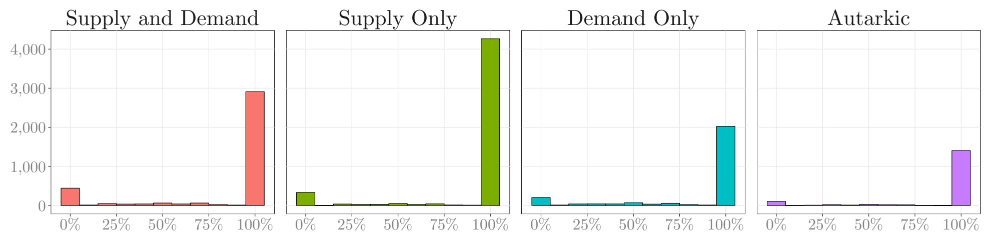
Turning to the cropping activities of the farm-households, we also observe heterogeneity. First, we note that households specializing in farming activities (Demand only) exhibit the highest value for crops output, with an average of $7,771$ Rupees. This



Note: The maps show household per capita average annual net income at the district level for total income (left) and agricultural income (right).

FIGURE 2.3: Average Per capita Income by State of Farm-households)

measure includes both the amount of sold by-product and the value of the share of the production kept for self-consumption. The value of crop production is much lower for households that also work outside the family plot (Supply and Demand), with an average of $4,020$ Rupees and $2,564$ Rupees for households engaging in off-farm work and not hiring people to work on their family plot (Supply Only). However, no such distinction can be observed regarding the share of produced crops that are kept for self-consumption. On average, 87% of the by-product is kept by families. When looking at the distribution of the percentage of kept production, we can distinguish between three types of behaviour (fig. 2.4): the vast majority of households keep the complete production (83.7%), a tiny share of households sell it (8.2%), and the remainder (8.1%) keep some of the production and sell the rest.



Notes: Agricultural households are divided into four labour regimes: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.4: Distribution of Percentage of Crops Kept for Self-Consumption

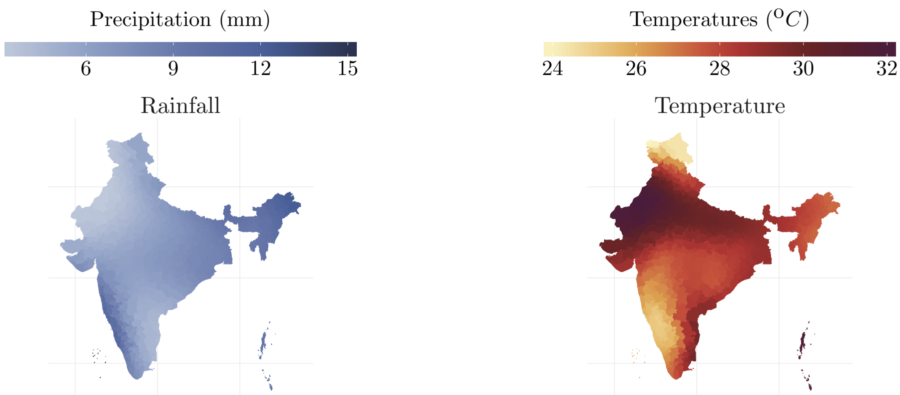
4.2 Climate

Climate conditions directly affect the agricultural production function. Consumption decisions may also be altered by varying climate conditions. We therefore incorporate climate data in our analysis using weather daily data from the National Climatic Data Center (NCDC) / National Oceanic and Atmospheric Administration (NOAA). We use two climate variables in the analysis: total rainfall and average temperature. Both are expressed as "climate normals", *i.e.*, as the 30-year observed average value.

Our aim is to define climate variables both at the same geographical and temporal unit as that for households, *i.e.*, at the district level, for a given year. Hence, in a first step, we interpolate daily weather station data at the district level by means of thin-plate splines (see, *e.g.*, Di Falco et al., 2011; Boer, 2001; Hutchinson, 1995).

In a second step, daily observations are averaged on a monthly basis.

The monthly averages are used in the third step to calculate the monthly "climate normals". We use a 30-year period (1980–2009) to compute monthly averages of both rainfall and temperature, at the district level. Figure 2.5 displays these (yearly aggregated) "normals".



Note: The maps depict the district-level "climate normals", *i.e.*, 30-year averages, for precipitation (left panel) and temperatures (right panel), for India.

Figure 2.5: Climate Normals (1980–2008)

Climate variations are expected to influence agricultural production, some climate conditions being more conducive to agricultural activities than other. The correlation between crops output (in Indian Rupees) and rainfall or temperature (30-year averages) are reported in table 2.2. As shown in the table, crops output is negatively correlated with temperatures, although the values are close to zero. Correlation with rainfall, on the other hand, exhibit higher even if limited values. In addition, disparities can be observed among the different labour regimes. Crops output in autarkic families seem to be more sensitive to rainfall variations than the rest of agricultural households. The same patterns are also observed in the correlation between net agricultural income and "climate normals".

TABLE 2.2: Correlations of Crops Output and Agricultural Income with Climate Variables

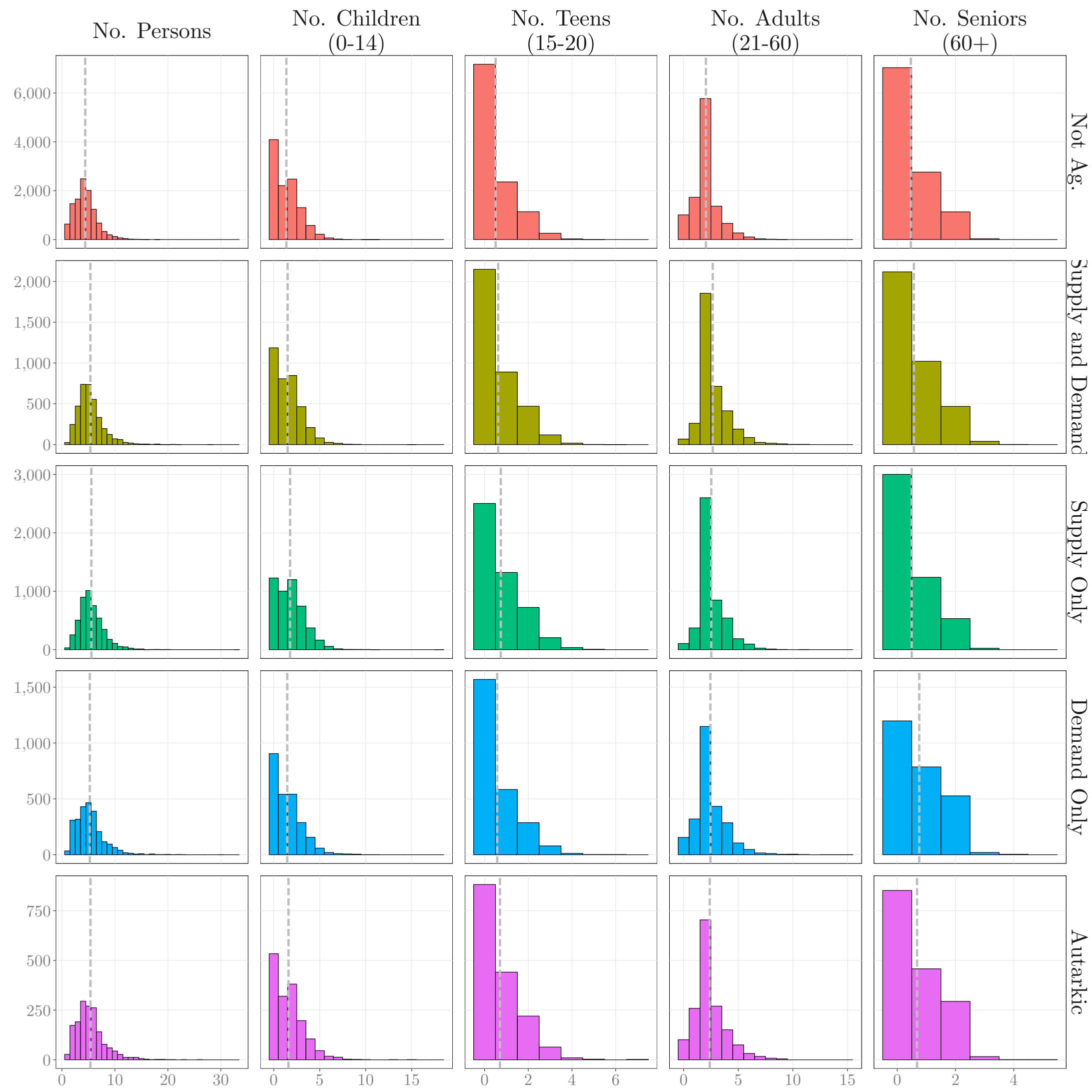
	Crops Output		Net Ag. Income	
	Rainfall	Temperatures	Rainfall	Temperatures
Supply and Demand	-0.16	-0.04	-0.10	-0.08
Supply Only	-0.18	-0.03	-0.16	-0.11
Demand Only	-0.14	-0.04	-0.11	-0.04
Autarkic	-0.24	-0.04	-0.20	-0.04

Notes: The statistics provided in the table concern farm-househols only. Agricultural households are divided into four categories according to their participation in the job market. These four categories are: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

4.3 Household Characteristics

The average Indian farm-household is composed of 5.4 family members, which is one more than the average for households with no agricultural activity (table 2.1). The decomposition by age and labour regime is depicted in fig. 2.6. The shape of the distribution of the number of children, teens, adults and seniors looks the same in all labour regimes. However, the skewness of families classified as "Supply Only", where at least one member engages in off-farm work and where no labour off-family is used to work on the farm, is higher than that of other type of households.

The average age in Indian rural household is 39.4 years old, for both agricultural and non agricultural households. It is noteworthy that this average is quite different for families classified as "Supply Only" and "Demand Only". In fact, in the former case, where households engage in work outside the farm plot and do not hire non-family labour, the average age is lower, with a value of 37.76 years old. This is explained by the higher average number of children and teens in those households, compared to the others, that drives the average age down. On the other hand, in "Demand Only" households, *i.e.*, in households that do not engage in off-farm work and hire labour on their family plot, the average age is higher. The number of children and teens also helps to explain why, as it is lower in those households. In addition, the number of



Notes: The vertical grey dashed line represents the sample mean for each category. Agricultural households are divided into four labour regimes: “Supply and Demand”, if they both engage in off-farm work and hire labour on their family plot; “Supply only”, if they engage in off-farm work and do not hire any labour on their family plot; “Demand only”, if they do not engage in off-farm work and hire labour on their family plot; and “Autarkic”, if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.6: Distribution of Number of Family Members

elderly is higher in those households: 0.76 on average, compared to 0.59 in all farm-households.

4.4 Other characteristics

The texture or the proportions of different-sized mineral particles contained in the soil alter the production of cereals. It is thus important to include measures of the quality of the environment that farmers face to grow crops. Soil quality heterogeneity is addressed using a worldwide $21,600 \times 43,200$ raster database of soil characteristics from the Harmonized World Soil Database (Batjes et al., 2008). From the grid data, we compute district averages of five variables relative to the texture of topsoil: gravel content by volume, sand, silt ,clay fraction, and organic carbon as a percentage of weight.

5 Estimation Results

This section first presents the estimation results of the agricultural production function and the resulting shadow wage, then turns to the analysis of the consumption decisions of farm-households, and finally presents the different demand elasticities.

5.1 Production

The results of the estimation of the agricultural production function represented by eq. (2.4) are presented in table 2.3.

The agricultural production is estimated first by OLS. Then, the endogeneity problem caused by labour decisions is taken into account using instrumental variables. The sample bias linked to the decision households must face on whether or not to take part in agricultural activities is addressed using a two-step Heckman procedure. The determining factors of this participation are reported in table 2.4.

Overall, the estimates are mostly similar in sign across all three methods investigated, but the magnitudes may change drastically once endogeneity and sample bias problems are considered.

In more details, we first observe that variable inputs (hours worked either by family members or by employees) and quasi-fixed inputs (cultivated area) have, as expected, a positive impact on the agricultural production. The magnitude of these effects differs depending on the estimation method. Once the model accounts for the endogeneity of the number of hours worked either by family members or by hired labour force as well as the sample section bias, the magnitude of the effect of the number of hours worked substantially rises. In fact, the production elasticity of family labour goes from 0.077 to 0.268, while the elasticity of hired labour rises from 0.048 to 0.176. For cultivated surface, the estimate obtained using the 2-steps Heckman procedure reveals an elasticity of 0.322.

Household characteristics also play a significant role in the variations of the agricultural production function. First, the age of the head of the household, which is commonly used as a proxy for the skills of the head of the family, has a significant effect on production. Besides, the older the head of the household, the higher the probability of the household to engage in farming activities, up to a threshold of 61 years old, above which any additional year decreases this probability. The second household characteristic that affects the production function as well as the participation in the agricultural market is the gender of the head of the household. The OLS estimate informs that having a man as the head of the household instead of woman increases the agricultural production. However, once the endogeneity problem caused by the decision of the level of labour force needed in the farm plot is addressed, and once the sample selection biased is accounted for, the story is quite different. We first notice that households whose head is a woman tend to engage less in agricultural activities. For households in the selected sample, *i.e.*, those engaged in farming activities, having a woman as the head of the household tend to increase the agricultural output.

Regarding location characteristics, the estimation results show a negative relationship between the output and the distance from the village to the nearest PDS shop or to the nearest Pucca road. The percentage of households with electricity in the village positively affects the agricultural production, but in the mean time, it reduces the probability of engaging in agricultural activities. Soil quality variables included to take soil heterogeneity into account also exhibit significant effects.

Finally, climate variables affect the agricultural production of Indian farm-households. The relationship between agricultural production and rainfall measured at their 30-year average has a U-shape form, while the relationship with temperatures also measured at their 30-year average displays an inverted U-shape relationship. Hence, a one millimetre increase in precipitation average level leads to a decrease in agricultural outputs up to a certain threshold, of 2.80 mm (within the range of observed values), above which the increase in precipitation has a positive effect on production. For temperatures, a one degree increase in the 30-year average value becomes harmful to the agricultural production for initial temperatures above the threshold of 17.23 Degree C, which is within the range of observed values.

The coefficient associated with the number of hours worked by the family members on the farm plot is used to calculate the shadow wage as explained in eq. (2.5). This shadow wage is then used in the estimation of the demand system.

TABLE 2.3: Production Function Estimation Results

	OLS		IV		Probit Selection	
	Coef	t-value	Coef	t-value	Coef	t-value
Intercept	1.379	(0.862)	2.634	(0.966)	2.522	(1.360)
Log of HH Hours on Farm	0.077***	(8.533)	0.601***	(3.666)	0.268***	(27.286)
Log of Hired Hours on Farm	0.048***	(14.479)	0.160.	(1.710)	0.176***	(49.900)
Log of Cultivated Area	0.507***	(58.433)	0.241.	(1.854)	0.322***	(34.463)
Age of the Head of HH	0.006	(1.435)	−0.012.	(−1.879)	−0.025***	(−4.349)
Age Sq. of the Head of HH $\times 10^4$	−0.422	(−1.161)	1.022.	(1.860)	2.013***	(3.954)
Gender (Male)	0.071**	(2.653)	−0.041	(−0.991)	−0.107**	(−2.906)
Log of Dist. to Nearest PDS	−0.002	(−0.160)	−0.007	(−0.418)	−0.032.	(−1.804)
Log of Dist. to Pucca Road	−0.001	(−0.355)	−0.010*	(−2.045)	−0.013**	(−3.058)
Pct. of HH with Electricity	0.005***	(12.550)	0.004***	(6.883)	0.005***	(11.034)
Gravel Content	0.007.	(1.759)	0.011*	(2.370)	0.005	(1.151)
Sand Fraction	0.016***	(11.395)	0.024***	(6.606)	0.020***	(12.354)
Silt Fraction	0.020***	(6.056)	0.017***	(4.339)	0.017***	(4.585)
Base Saturation	0.007***	(4.685)	0.019***	(4.671)	0.012***	(6.881)
Rainfall	−0.600***	(−4.123)	−0.981***	(−4.948)	−0.891***	(−5.479)
Rainfall Squared	0.089***	(3.674)	0.189***	(4.532)	0.159***	(5.848)
Temp.	0.439**	(3.269)	−0.005	(−0.025)	0.323*	(2.144)
Temp. Squared	−0.011***	(−3.986)	−0.003	(−0.633)	−0.009**	(−2.934)
Adj. R-Squared	0.47		0.29			

Notes: $N = 12,206$. Significance levels are denoted by a dot (˙) at the 10% level, one asterisk (*) at the 5% level, two asterisks (**) at the 1% level and three asterisks (***) at the .1% level. HH denotes Household. Hours on farm are instrumented using the following variables: No. Female Children (0-14), No. Male Children (0-14), No. Female Seniors (60+), No. Male Seniors (60+), Price of Pure-market Goods. The identification variables used in the first stage of the two-step Heckman estimation are: No. Children (0-5), No. Children (6-14), No. Working Age (15-60). Hours on farm in the second step are instrumented as in the IV estimation.The coefficients of state dummies are not reported in the table for clarity purposes. They are however available upon request.

5.2 Consumption

Using the shadow price estimated using the production function results, we are able to examine the budget shares of Indian agricultural households. We analyse how households allocate the amount of their full income among four different goods: pure market goods, crops that can be home-grown, animal products, and leisure, as as previously stated in section 3.3. The share of each alternative in the full income as well as the associated unit price are reported in table 2.5. On average, leisure represents 23.81% of full income, crops represents 34.78%, animals 24.68% and pure market goods come last with a share of 16.73% of full income. The share of crops consumption varies with the type of household. On average, households classified as "Supply Only" devote a larger share of their full income to crops consumption (37.97%) than the other type of households and in the mean time, a lower share of leisure (20.74%). On the contrary, households classified as "Demand Only", allocate a higher share of their full income to

Table 2.4: Participation in Agricultural Labour Market (Probit Selection Model)

	Estimate	(t-value)
	Coef	t-value
Intercept	-15.603***	(-7.906)
No. Children (0-5)	0.014	(0.198)
No. Children (6-14)	0.421***	(8.416)
No. Working Age (15-60)	0.148***	(23.376)
Age of the Head of HH	0.067***	(14.858)
Age Sq. of the Head of HH $\times 10^4$	-5.222***	(-12.210)
Gender (Male)	0.487***	(18.435)
Log of Dist. to Nearest PDS	0.142***	(7.271)
Log of Dist. to Pucca Road	0.046***	(8.295)
Pct. of HH with Electricity	-0.003***	(-6.421)
Gravel Content	0.012**	(2.737)
Sand Fraction	0.003	(1.541)
Silt Fraction	0.007.	(1.863)
Base Saturation	-0.001	(-0.819)
Rainfall	0.597***	(3.929)
Rainfall Squared	-0.107***	(-4.358)
Temp.	0.828***	(5.089)
Temp. Squared	-0.015***	(-4.353)

Notes: $N = 10,686$. Significance levels are denoted by a dot (˙) at the 10% level, one asterisk (*) at the 5% level, two asterisks (**) at the 1% level and three asterisks (***) at the .1% level. HH denotes Household. The coefficients of state dummies are not reported in the table for clarity purposes. They are however available upon request.

leisure (28.68%) than the rest of the households, and a lower share to crops consumption (29.93%). This may be explained by the higher value of the shadow wage for "Demand Only" households: the opportunity cost of not working is higher for these families.

These shares and prices are used to estimate the Ideal Demand System described by eq. (2.6). The results are reported in table 2.6.

5.3 Elasticities

The elasticities computed from the AIDS estimates are reported in table 2.7.

The demand for crops is almost inelastic. It is estimated at 0.176 for all rural households. Among the different types of households, "Demand Only", for which the share of crops in total expenditures is the highest, are those for which this demand elasticity is the lowest (0.139). Animal-derived products are identified as luxury goods, since the income elasticity for these goods is estimated at 1.3 for all rural households. The elasticity of demand for these animal products is low for all types of rural households (0.384). Households classified as "Supply and Demand" respond less to price variation

Table 2.5: Consumption Choices According to the Different Labour Regimes

	All Ag.	Supply and Demand	Supply Only	Demand Only	Autarkic
Consumption Expenditures					
Market Goods Exp. (INR/Cap.)	6,417.86	6,135.79	5,665.59	7,579.50	7,467.17
Crops Exp. (INR/Cap.)	13,501.60	13,821.63	12,460.19	14,807.33	13,883.87
Animals Exp. (INR/Cap.)	12,149.35	10,949.53	9,939.82	15,454.34	16,195.18
Leisure Exp. (INR/Cap.)	16,283.35	15,109.80	9,529.90	28,101.60	20,653.06
Consumption Shares					
Pure-market Goods (%)	17.27	17.22	18.08	16.11	16.75
Crops (%)	35.91	36.91	39.09	31.08	31.75
Animals (%)	25.50	24.78	24.41	26.85	28.16
Leisure (%)	21.33	21.09	18.42	25.95	23.34
Unit Price					
Price of Pure-market Goods (INR per unit)	63.01	62.91	63.43	62.39	62.95
Price of Crops (INR per unit)	29.38	29.91	28.22	30.39	30.13
Price of Animal Products (INR per unit)	46.10	52.95	41.38	48.56	41.50
Shadow Wage (INR per Hour)	2.51	2.53	1.98	3.42	2.65
No. obs.	12,216.00	3,454.00	4,715.00	2,445.00	1,602.00
% of Agricultural Households	100%	28.3%	38.6%	20%	13.1%

Notes: The statistics provided in the table concern farm-househols only. Agricultural households are divided into four categories according to their participation in the job market. These four categories are: “Supply and Demand”, if they both engage in off-farm work and hire labour on their family plot; “Supply only”, if they engage in off-farm work and do not hire any labour on their family plot; “Demand only”, if they do not engage in off-farm work and hire labour on their family plot; and “Autarkic”, if they neither engage in off-farm work nor hire labour on their family plot.

of these animal-derived products than the other types of households. Higher crops prices lead to a weak increase in the demand for animal-derived products, and a relatively higher increase in the demand for pure market goods, for all types of households. On the contrary, higher crops prices lead to a decrease in the demand for leisure. The case of leisure is puzzling. According to the classical theory, if leisure is a normal good, a relative increase in its price should lead to a relative decrease in its demand. Recall that the price of leisure is the shadow price of labour and that farmers allocate their available time either on work or on leisure, so that the elasticity of leisure demand can be interpreted as the elasticity of labour supply. The classical theory indicates that this elasticity should be positive: when the wages rise, the labour supply should rise as well. Our results suggest the opposite. The elasticity of leisure is positive for all types of farms, implying a negative labour supply elasticity. Households classified as “Demand Only”, and “Autarkic”, *i.e.*, the two types of households that do not engage in off-farm work have relatively more inelastic labour supply. Different explanations regarding the negative sign of these supply elasticities emerge in the literature. Dessing (2002) argued that at low wages, leisure can be considered as a luxury good and that the income effect dominates, thus leading to a negative labour supply elasticity.

Berg (1961) argued that these negative labour supply elasticities could be explained by the fact that once the minimum level of subsistence income is reached, poor households reduce their work. In India, Dasgupta and Goldar (2006) found a negative labour supply elasticity for women from households below the poverty line.

5.4 Scenarios

To get a better perspective of the potential effects of either price changes or climate changes on the consumption decisions of Indian rural households, we test different scenarios.

The strategy we use consists in comparing the predicted consumption quantities of each of the four goods (pure-market, crops, animals and leisure) obtained using the estimates of the AIDS model, to the predicted quantities calculated once either prices or climate values have been modified. The predictions are calculated for all agricultural households as well as for each subset based on the households' labour regime. This method gives an insight of the link between prices and consumption, and on climate and consumption, but should not be viewed as a forecasting exercise.

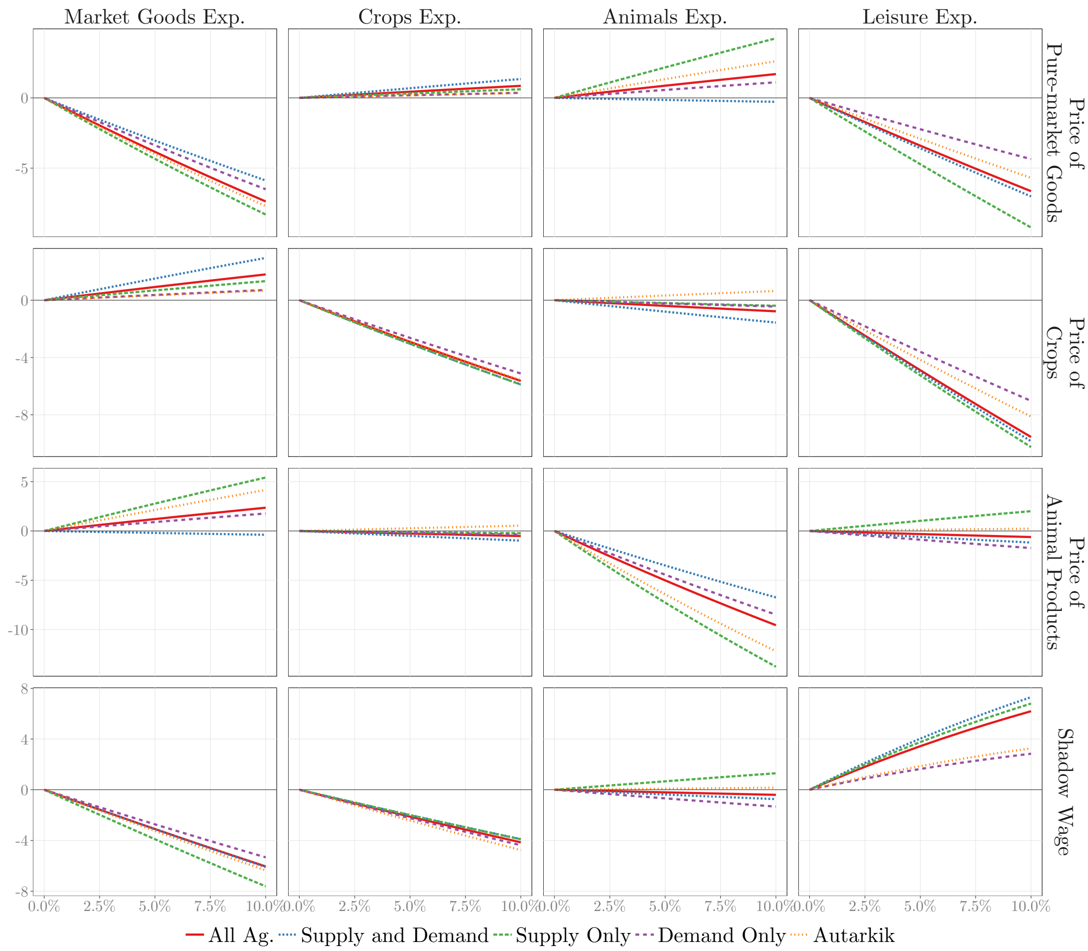
We first present some price scenarios and then turn to climate scenarios.

5.4.1 Changes in Prices

First, we gradually increase the price of each good, separately, and observe the impacts on the consumption of each good. This gives a more visual representation of the elasticities reported in table 2.7. The results are plotted in fig. 2.7. Each column of the panel of graphs indicates how the consumption of the corresponding item is altered by a gradual increase in the price of the good.

5.4.2 Changes in Climate

Different climate scenarios are envisaged. First, we alter precipitation statistics only, by considering variations from -30% to $+30\%$ of the amount of total rainfall experienced on average during the last 30 years. Then, we isolate the potential effect of temperature on consumption patterns, by assessing an increase up to $5°$C. Finally, we assess the combined effect of a change in both precipitation and temperature.



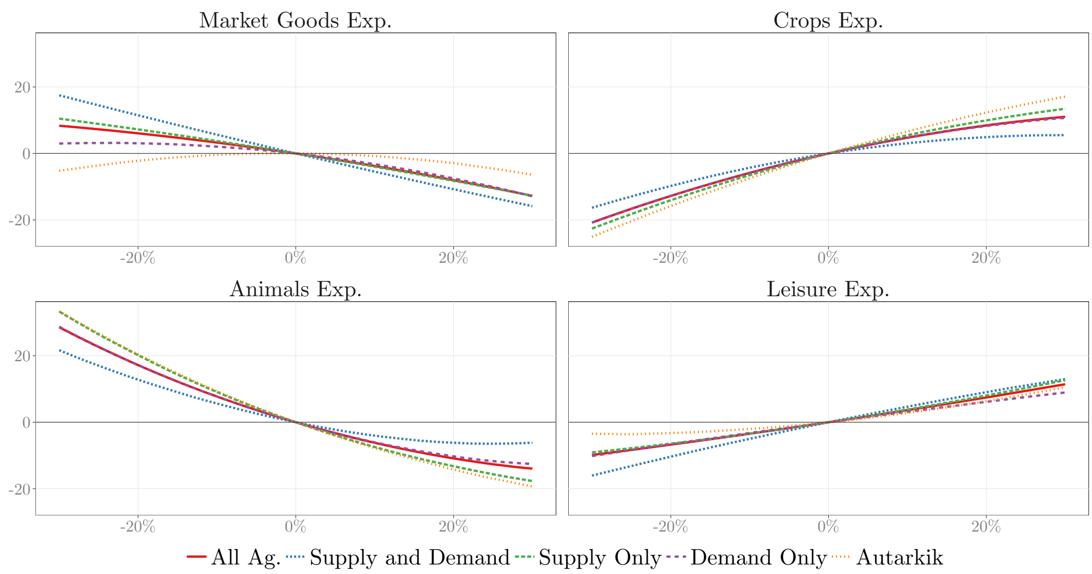
Notes: The graphs show the effects of an increase in each commodity prices (separately) on the share of consumption of each good, in each different labour regimes. The x-axis gives the temperature increase in degree, while the y-axis gives the median percent change in the consumption share. Agricultural households are divided into four labour regimes: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.7: Effects of Increasing Prices on Consumption Shares (Median Percent Changes)

The effects of varying levels of rainfall on household decisions of consumption are plotted in fig. 2.8. Each panel corresponds to the evolution of the share of consumption of one of the four goods with respect to the modification of the level of precipitation. The solid red line corresponds to the median percent change in the share of consumption,[4] while the four other lines depict the change in these shares according to the labour regime of the households. Overall, households show a similar response to precipitation changes., *i.e.*, an increase in the share of pure-market goods and animal products and a decrease in crops consumption and in leisure time following a decrease in precipitation, and opposed effects following an increase in precipitation.

[4]The median percent change is used rather than the average percent change as some small changes starting from low shares inflate the value of the average change.

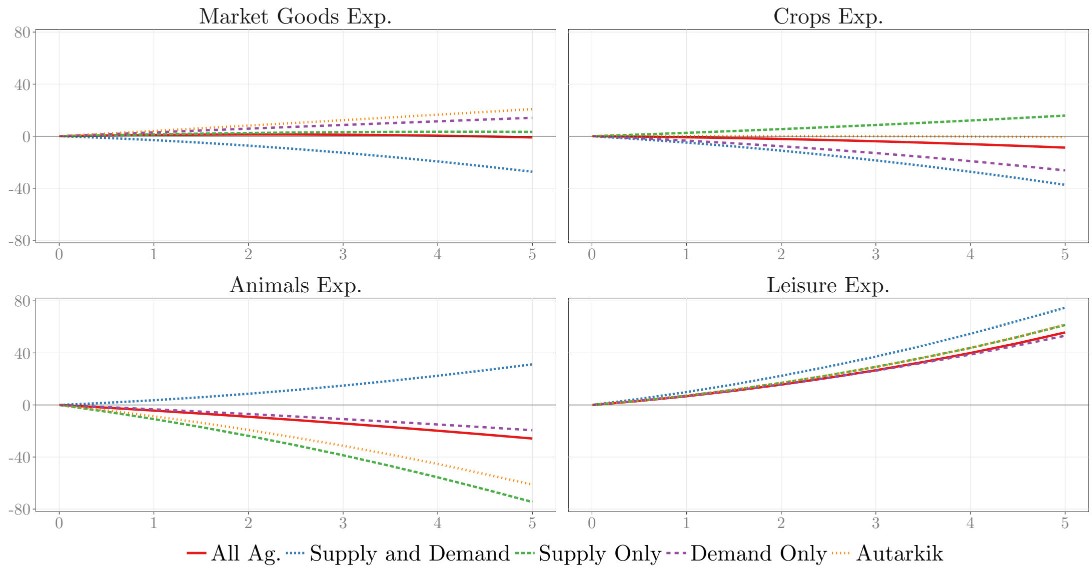
Having said that, a distinction between two types of households can be drawn. The magnitude of the response of households to an increase or a decrease in total rainfall clearly differs between households that both supply and demand labour, and autarkic households. The latter type of households is less affected by varying climate conditions in regards with the consumption of non-agricultural goods, but shows a more substantial response in regards with the consumption of both crops and animal products.



Notes: The graphs show the effects of a variation in precipitation levels on consumption of each good, in each different labour regimes. The x-axis gives the percent change in precipitation levels, while the y-axis gives the median percent change in consumption. Agricultural households are divided into four labour regimes: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.8: Effects of Precipiation Variations on Consumption (Median Percent Changes)

In the same way as for the precipitation changes, fig. 2.8 shows the response in the consumption decisions of Indian agricultural households to a change in temperature. Overall, the consumption of pure-market goods is not affected much by the increase. However, once breaking down households according to their participation in the labour market, we observe that the share of pure-market goods consumed by households that both supply and demand labour force is negatively affected by the increase in temperature while the other types of households exhibit an opposed response. Concerning crops consumption, we observe that autarkic households seem to be unaffected by an increase in 30-year average temperature. On the contrary, households both providing and demanding labour as well as households that demand only labour are gradually decreasing their share of crops consumption as temperature increases.



Notes: The graphs show the effects of an increase in temperature levels on the consumption of each good, in each different labour regimes. The x-axis gives the temperature increase in degree, while the y-axis gives the median percent change in consumption. Agricultural households are divided into four labour regimes: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.9: Effects of Increasing Temperatures on Consumption (Median Percent Changes)

Figure 2.10 offers another insight on the relationship between consumption shares and climate. It shows how the different types of households, based on their labour regime, respond to a modification of both precipitation and temperature. Each line of the matrix of plots corresponds to a type of household, and each column indicates the variation of the share of consumption of one of the four commodities (pure market goods, crops, animal-derived products, and leisure). There is a lot of heterogeneity in the results. Some patterns regarding agricultural products consumption seem to emerge. When pooling all households, we note a trade-off between the consumption of crops and animal products. If the level of rainfall decreases, the share of crops consumption decreases as well, while, in the mean time, the share of animal products rises. When households are divided according to their labour regime, the same trade-off is observed for each regime.

6 Concluding remarks

The prospect of a warmer global climate with increased climate variability and changing precipitation patterns across the world defines new challenges to research on production and consumption behaviour in developing countries. In fact, there is a broad consensus that the poorest share of the world's population is most vulnerable to these predicted changes. The way on how climate change and climate variability affects households in developing countries depends not only on direct impacts on productivity of agriculture (effect on crop yields), but on indirect impacts on consumption behaviour.

This study provides a cross-sectional analysis of the demand of Indian households farms, relying on the household modelling to investigate the current impact of climate variables on consumption behaviour. We first examine the response of agricultural production to climate variations, using a large data set of agricultural households in India. From this estimation, we calculate the shadow price of labour which can then be fed into an Almost Ideal Demand System aiming at analysing the consumption demand of Indian farm-households. Changes in consumption decisions following a change in prices or in climate values reflecting different climate scenarios are then studied. The results show that the agricultural production is sensitive to both precipitation and rainfall. Consumption decisions are also affected by climate conditions. In particular, an increase in total rainfall leads to a higher demand for pure market goods and animal derived products, and a decrease in crops and leisure. In addition, crops demand is more affected by the variation in rainfall for autarkic households relative to other types of rural households. On the contrary, the demand for crops products of autarkic households is less affected by varying temperatures. The scenarios in which both rainfall and temperatures are changed exhibit a trade of between crops and animal-derived products.

The framework used in this chapter considers first the production decisions of farm households, and then turns to the consumption decisions. It would be interesting to model both decisions in a single model. This strategy makes sense when market imperfections are suspected (De Janvry et al., 1991; Sadoulet et al., 1998; Taylor and Adelman, 2003). As long as markets are perfect, households are indifferent to consuming own-produced and market-purchased goods. However, when markets fail for a households, separability does not hold any more and the household's production and consumption decisions should be solved simultaneously (Singh et al., 1986).

Another idea to consider is the transformation of crop production in calories as performed by Auffhammer and Schlenker (2014). This conversion would provide an insight on food security, and help targeting farm households that are more at risk because of climate change.

TABLE 2.6: Almost Ideal Demand System Results

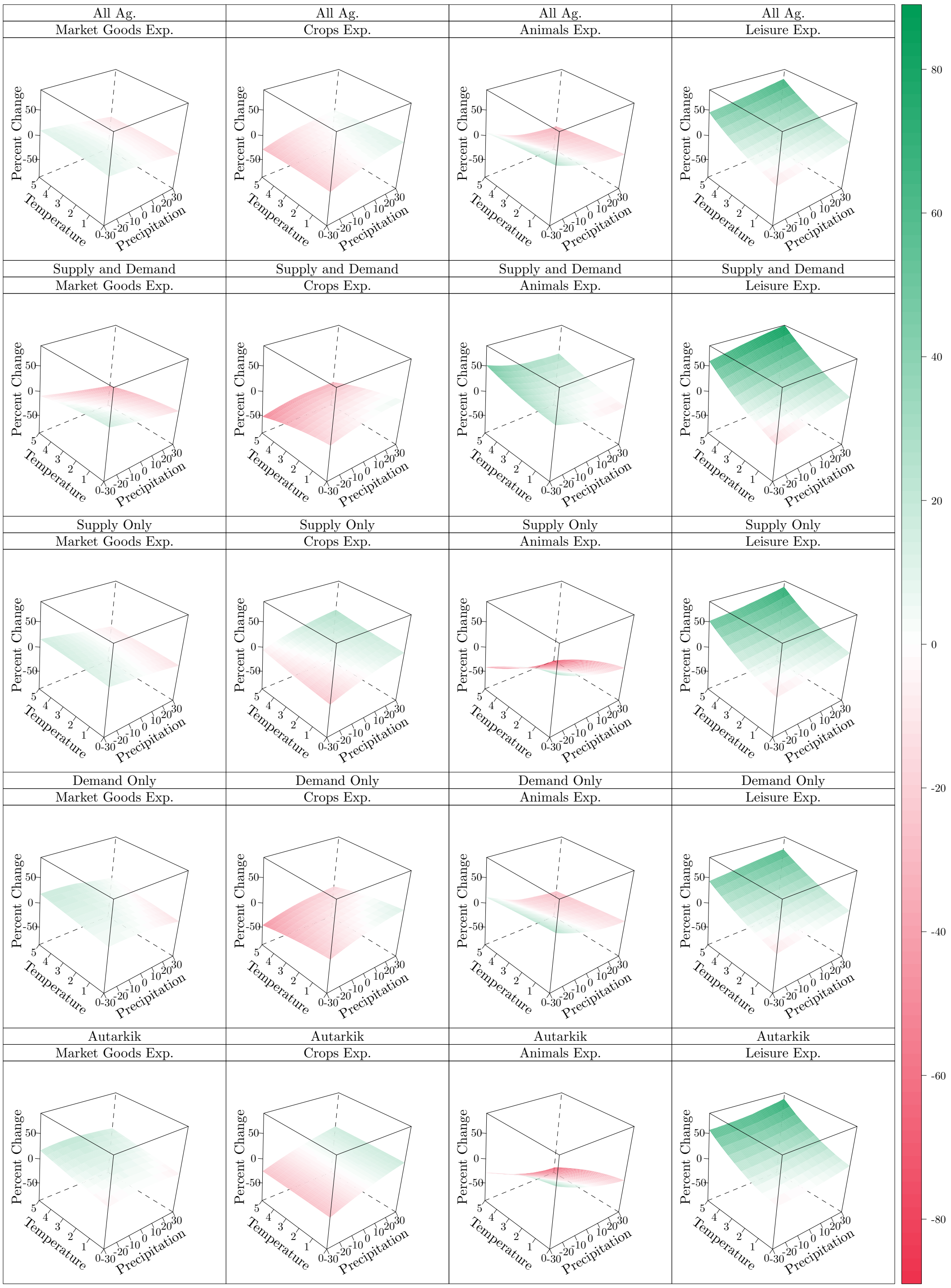
	$i = m$		$i = c$		$i = a$		$i = L$	
	Coef	t-value	Coef	t-value	Coef	t-value	Coef	t-value
	Supply and Demand ($N = 3,454$)							
β_i	−0.023	(−0.216)	−1.503***	(−8.732)	0.522*	(2.562)	2.004***	(25.448)
δ_i	−0.064***	(−22.952)	−0.025***	(−5.594)	0.087***	(18.275)	0.002	(0.629)
γ_im	0.067***	(7.593)	0.056***	(6.575)	−0.007	(−0.667)	−0.116***	(−23.048)
γ_ic	0.056***	(6.575)	0.148***	(12.198)	−0.041***	(−5.752)	−0.163***	(−35.013)
γ_ia	−0.007	(−0.667)	−0.041***	(−5.752)	0.068***	(3.905)	−0.019***	(−3.646)
γ_iL	−0.116***	(−23.048)	−0.163***	(−35.013)	−0.019***	(−3.646)	0.299***	(86.948)
Rainfall	−0.048***	(−4.121)	0.232***	(11.739)	−0.228***	(−10.318)	0.044**	(2.875)
Rainfall Squared (×10)	0.020	(1.129)	−0.318***	(−10.279)	0.326***	(9.449)	−0.029	(−1.211)
Temp.	0.055***	(5.832)	0.115***	(8.047)	−0.079***	(−4.771)	−0.091***	(−12.276)
Temp. Squared (×10)	−0.011***	(−5.558)	−0.025***	(−8.228)	0.017***	(4.652)	0.020***	(12.493)
Crops Kept	−0.008*	(−2.424)	0.010·	(1.746)	−0.008	(−1.196)	0.006	(1.282)
R-Squared	0.84		0.85		0.81		0.95	
	Supply Only ($N = 4,715$)							
β_i	0.194·	(1.918)	−0.115	(−0.609)	−1.702***	(−8.380)	2.623***	(21.506)
δ_i	−0.054***	(−17.347)	−0.024***	(−5.157)	0.102***	(24.096)	−0.024***	(−3.965)
γ_im	0.017*	(2.121)	0.026**	(3.057)	0.107***	(9.661)	−0.151***	(−25.085)
γ_ic	0.026**	(3.057)	0.151***	(18.975)	−0.010	(−0.844)	−0.168***	(−29.715)
γ_ia	0.107***	(9.661)	−0.010	(−0.844)	−0.131***	(−5.141)	0.033*	(2.066)
γ_iL	−0.151***	(−25.085)	−0.168***	(−29.715)	0.033*	(2.066)	0.286***	(28.092)
Rainfall	−0.010	(−1.040)	0.281***	(17.876)	−0.269***	(−15.645)	−0.002	(−0.187)
Rainfall Squared (×10)	−0.037*	(−2.421)	−0.359***	(−13.759)	0.351***	(12.384)	0.045*	(2.330)
Temp.	0.020*	(2.523)	−0.022	(−1.627)	0.108***	(6.207)	−0.106***	(−16.476)
Temp. Squared (×10)	−0.003·	(−1.946)	0.006*	(2.180)	−0.026***	(−6.818)	0.023***	(16.369)
Crops Kept	−0.008*	(−2.165)	0.005	(0.713)	−0.005	(−0.722)	0.008·	(1.740)
R-Squared	0.78		0.77		0.73		0.93	
	Demand Only ($N = 2,445$)							
β_i	0.155	(1.106)	−0.830***	(−3.882)	−0.269	(−0.984)	1.944***	(17.566)
δ_i	−0.043***	(−16.323)	−0.042***	(−9.554)	0.081***	(15.279)	0.004	(1.007)
γ_im	0.051***	(6.051)	0.013	(1.433)	0.032**	(3.011)	−0.096***	(−19.677)
γ_ic	0.013	(1.433)	0.155***	(13.963)	−0.013	(−1.133)	−0.155***	(−27.800)
γ_ia	0.032**	(3.011)	−0.013	(−1.133)	0.019	(0.824)	−0.038***	(−5.563)
γ_iL	−0.096***	(−19.677)	−0.155***	(−27.800)	−0.038***	(−5.563)	0.289***	(68.596)
Rainfall	0.057***	(4.448)	0.230***	(11.765)	−0.323***	(−13.152)	0.036*	(1.978)
Rainfall Squared (×10)	−0.147***	(−7.137)	−0.305***	(−9.541)	0.471***	(11.704)	−0.019	(−0.651)
Temp.	0.007	(0.581)	0.072***	(4.092)	0.010	(0.435)	−0.089***	(−10.214)
Temp. Squared (×10)	−0.000	(−0.153)	−0.016***	(−4.232)	−0.004	(−0.742)	0.020***	(10.697)
Crops Kept	−0.006	(−1.375)	0.017*	(2.366)	−0.006	(−0.663)	−0.005	(−0.768)
R-Squared	0.89		0.91		0.86		0.96	
	Autarkic ($N = 1,602$)							
β_i	0.047	(0.265)	−0.212	(−0.723)	−1.532***	(−3.908)	2.696***	(15.855)
δ_i	−0.036***	(−9.255)	−0.036***	(−6.821)	0.086***	(13.384)	−0.014*	(−2.146)
γ_im	0.029**	(2.643)	0.013	(1.089)	0.078***	(5.332)	−0.119***	(−19.908)
γ_ic	0.013	(1.089)	0.138***	(9.875)	0.019	(1.111)	−0.170***	(−22.699)
γ_ia	0.078***	(5.332)	0.019	(1.111)	−0.102**	(−2.811)	0.005	(0.297)
γ_iL	−0.119***	(−19.908)	−0.170***	(−22.699)	0.005	(0.297)	0.284***	(28.709)
Rainfall	0.104***	(5.491)	0.245***	(8.757)	−0.310***	(−8.901)	−0.039·	(−1.749)
Rainfall Squared (×10)	−0.229***	(−6.856)	−0.297***	(−5.912)	0.406***	(6.466)	0.120**	(3.075)
Temp.	0.004	(0.301)	0.010	(0.442)	0.110**	(3.249)	−0.125***	(−10.830)
Temp. Squared (×10)	0.001	(0.171)	−0.002	(−0.385)	−0.026***	(−3.560)	0.027***	(10.996)
Crops Kept	−0.002	(−0.337)	0.005	(0.503)	−0.008	(−0.594)	0.005	(0.580)
R-Squared	0.92		0.94		0.91		0.98	

Notes: The estimated coefficients are described in eq. (2.6). The subscripts m, c, a, and L refer to market goods, crops, animal products, and leisure, respectively. All agricultural households are furthermore divided into four categories according to their participation in the job market. These four categories are as follows: “Supply and Demand”, if they both engage in off-farm work and hire labour on their family plot; “Supply only”, if they engage in off-farm work and do not hire any labour on their family plot; “Demand only”, if they do not engage in off-farm work and hire labour on their family plot; and “Autarkic”, if they neither engage in off-farm work nor hire labour on their family plot.Significance levels are denoted by a dot (·) at the 10% level, one asterisk (*) at the 5% level, two asterisks (**) at the 1% level and three asterisks (***) at the .1% level.

Table 2.7: Elasticities

	Marshallian (Compensated) Price				Hicksian (Uncompensated) Price				Demand
	p_m	p_c	p_a	p_L^*	p_m	p_c	p_a	p_L^*	Expend.
					All Agricultural Households				
C_m	−0.569***	0.417***	0.007	−0.561***	−0.447***	0.670***	0.187***	−0.410***	0.705***
C_c	0.171***	−0.499***	−0.145***	−0.428***	0.327***	−0.176***	0.085***	−0.236***	0.900***
C_a	−0.098***	−0.352***	−0.734***	−0.185***	0.138***	0.139***	−0.384***	0.107***	1.370***
C_L	−0.520***	−0.759***	−0.081***	0.395***	−0.353***	−0.413***	0.165***	0.601***	0.965***
					Supply and Demand				
C_m	−0.296***	0.547***	−0.306***	−0.572***	−0.188***	0.778***	−0.151***	−0.440***	0.627***
C_c	0.209***	−0.559***	−0.159***	−0.423***	0.370***	−0.215***	0.072**	−0.227***	0.932***
C_a	−0.325***	−0.374***	−0.477***	−0.176***	−0.092*	0.126*	−0.142***	0.109***	1.353***
C_L	−0.559***	−0.779***	−0.086**	0.415***	−0.385***	−0.407***	0.164***	0.628***	1.009***
					Supply Only				
C_m	−0.641***	0.347***	0.262***	−0.669***	−0.514***	0.621***	0.433***	−0.539***	0.701***
C_c	0.121***	−0.572***	−0.093***	−0.396***	0.291***	−0.205***	0.137***	−0.223***	0.939***
C_a	0.072·	−0.321***	−1.071***	−0.099***	0.329***	0.233***	−0.725***	0.163***	1.417***
C_L	−0.705***	−0.824***	0.033	0.626***	−0.548***	−0.484***	0.246***	0.786***	0.869***
					Demand Only				
C_m	−0.520***	0.270***	0.025	−0.506***	−0.402***	0.497***	0.222***	−0.317***	0.732***
C_c	0.122***	−0.408***	−0.127***	−0.453***	0.262***	−0.139***	0.105***	−0.229***	0.866***
C_a	−0.064·	−0.262***	−0.734***	−0.242***	0.146***	0.143**	−0.385***	0.096***	1.302***
C_L	−0.378***	−0.606***	−0.138***	0.108***	−0.215***	−0.291***	0.134***	0.371***	1.014***
					Autarkic				
C_m	−0.694***	0.239***	0.272***	−0.603***	−0.562***	0.488***	0.493***	−0.419***	0.785***
C_c	0.112**	−0.478***	−0.042·	−0.478***	0.260***	−0.197***	0.208***	−0.271***	0.886***
C_a	0.083·	−0.165**	−1.088***	−0.135***	0.302***	0.249***	−0.720***	0.170***	1.306***
C_L	−0.472***	−0.682***	−0.032	0.246***	−0.314***	−0.384***	0.232***	0.466***	0.940***

Notes: The subscript m, c, a, and L refer to pure market, crops, animals and leisure, respectively. Significance levels are denoted by a dot (·) at the 10% level, one asterisk (*) at the 5% level, two asterisks (**) at the 1% level and three asterisks (***) at the .1% level. The statistics provided in the table concern farm-households only. Agricultural households are divided into four categories according to their participation in the job market. These four categories are: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.



<u>Notes:</u> The graphs show the effects of a combined modification of precipitation and temperature on consumption of each good, in each different labour regimes. The x-axis gives the percent variation in temperature, the y-axis gives the temperature increase in degree, and the z-axis gives the median percent change in consumption. Agricultural households are divided into four labour regimes: "Supply and Demand", if they both engage in off-farm work and hire labour on their family plot; "Supply only", if they engage in off-farm work and do not hire any labour on their family plot; "Demand only", if they do not engage in off-farm work and hire labour on their family plot; and "Autarkic", if they neither engage in off-farm work nor hire labour on their family plot.

FIGURE 2.10: Effects of Climate Change on Consumption (Median Percent Changes)

Part II

Climate Change in Developed Countries

In the first two chapters, the focus is made on India, a developing country where the agricultural sector still represents a substantial share of its GDP. The second part of this thesis offers a complementary view on the effects of climate change on agriculture by considering developed countries rather than developing countries.

In developed countries, although the value added of agriculture in GDP is much lower than in developed countries, examining the effects of the climate and the weather on production is also essential. In fact, many developed economies are key actors in the world's agricultural production. In the context of a changing climate, it is important to quantify the effects of weather variations on crop production, especially as the FAO states that in order to feed the world population in 2050, food production should increase by 70 percent between 2005–07 and 2050 (Bruinsma, 2009). The third chapter thus looks into the relationship between the weather and the agricultural yields of two major crops in Europe, wheat and corn. These two crops account for about two third of Europe's cereal production. On the global market, according to the FAO, European production of corn accounted for 12% of production on average from 1990 to 2014, and for a third of global wheat production. It then appears necessary to investigate how these crops react to weather variability, and to quantify this response under different climate scenarios. To that end, the third chapter provides an empirical study of the response of wheat and corn yields to weather variability, using regional data from 1991 to 2009. The analysis incorporates the effects of production prices on yields in its framework, allowing for a different effect before and after the market reform that reduced price supports. Different climate scenarios are then envisaged to assess the potential response of wheat and corn yields to climate change.

The fourth chapter also considers the case of developed economies, but focuses on a smaller actor on agricultural markets. New Zealand is used as an illustrative example. New Zealand, is a small-open economy with a relatively important agricultural sector that accounts for around 7% of its GDP according to the World Bank. Its geographical area is relatively small ($268,838$ square kilometres), so that a weather shock affecting agriculture in the country can have significant impacts on national GDP. The fourth chapter investigates how these weather shocks affect the business cycles of a small open economy through a general equilibrium approach. To that end, a Dynamic Stochastic General Equilibrium Model (DSGE) is developed and then estimated using New Zealand data. Different climate scenarios are once again envisaged, to estimate the response of the economy to an environment where the variance of climate shocks is increased.

Chapter 3

Climate Change and Agricultural Yields: an European Case Study

Joint work with Catherine Benjamin (University of Rennes 1)

1 Introduction

Climate change may be one of the greatest threats facing the planet. The Intergovernmental Panel on Climate Change (IPCC), which includes more than $1,300$ scientists all around the world, shows in its last study (Edenhofer et al., 2014) that over recent years we observe increasing temperatures in various regions, and increasing occurrence and intensity in extreme weather events such as droughts and floods.

Climate change poses a major challenge to agriculture because of the critical dependence of the agricultural system on climatic variables such as temperature and precipitation. Over time, climate change is expected to increase the annual variation in crop and livestock production because of its effects on weather patterns and because of increases in some types of extreme weather events. There is an important literature focused on predicting and measuring the impact of climate change on agricultural systems in many countries around the world. A brand of that literature focuses on crop yields and adopts two complementary methods. Both are based on the production function approach, but one relies on crop-growth biophysical modelling while the other uses statistical methods.

Crop simulation models represent crop growth through mathematical equations as functions of soil conditions, the weather and management practices (Mearns et al., 1997). The mathematical models are calibrated from carefully controlled agronomic experiments (see, *e.g.*, Adams et al., 1998; Rosenzweig and Parry, 1994). Crops are grown in field or laboratory settings under different conditions. This process allows to calibrate the parameters of the mathematical model. Then, the model can be used to simulate crop growth under new climate conditions, reflecting climate change, for instance. The main shortcoming of these models is that they do not take into account adaptive behaviours of farmers. In fact, no changes are allowed to farming methods across experimental conditions so that all differences in outcomes are assumed to be due to only changes variables of interest (temperature, precipitation). Hence, the effects of climate change are probably overestimated (see *e.g.*, Adams et al., 1990; Parry et al., 2004).

This pitfall is partly overcome by statistical analyses. Rather than setting-up experiments to control some input variables, statistical analyses rely on historical observations on yields, using cross-sectional or panel data (see, *e.g.*, You et al., 2009; Schlenker and Roberts, 2009; Lobell et al., 2011). The variation of crop yields can be linked to the level of inputs, to farming practices, and also to varying weather conditions. The covered geographical area can be large, and not bounded to the experiment field as in biophysical models (Lobell and Burke, 2010).

However, both methods suffer from their failure to account for some changing behaviour of farmers. Neither biophysical nor statistical models will be able to catch a switch in crops grown or a change in activity if a change in the opportunity cost occurs. Mendelsohn et al. (1994) described this as the “dumb farmer scenario”, and therefore recommended to explore the relationship between climate and net revenues, rather than yields. The framework proposed by Mendelsohn et al. (1994), called the “Ricardian analysis”, is a hedonic model of farmland pricing that focuses on land value. The basic idea is that long run climate should be capitalized into land values: in a competitive market, the price of farm land reflects the discounted value of all the expected future profits that can derive from it. In this framework, farmers adaptation is implicitly accounted for. They adjust their decisions regarding the level of their inputs and outputs depending on the climate conditions they face. A handful of studies use the Ricardian analysis in European regions (Maddison, 2000; Lang, 2007; Lippert et al., 2009; García and Viladrich, 2009; De Salvo et al., 2013; Van Passel et al., 2016). The use of a Ricardian framework however implies a strong assumption regarding input and output prices. Both are assumed to remain unchanged due to the use of cross-sectional data, thus making it impossible to incorporate year-to-year fluctuations of production prices. Special attention should be given on that point as we observe high volatility of crop prices (Cline, 1996; Schlenker et al., 2005).

In addition, the Ricardian framework is built around agricultural profits and therefore does not look into the question of yield variability, which is important in the case of Europe. During the last decades, according to Eurostat data, crop yields have increased although the cultivated area has decreased. In the meantime, the variability of crop yields has also increased, partly due to the rise in the occurrence of adverse weather events.

Furthermore, a major feature in the European Union is the impact of the Common Agricultural Policy (CAP) on farmer behaviour. Over the last years, major changes in agricultural subsidies and environmental policies have been observed. The changing policies probably have impacted yields. For example, they might have lowered crop yields by reducing the incentive for intensive agriculture. They might also have lowered yields by restricting the use of fertilizers.

It then appears that the question of yield variability in Europe should be addressed. In most empirical work, the focus is made on the mean effect of the weather variability on crop yields. Some scholars suggest to drop the hypothesis of stationarity of weather variables and to examine how weather variables affect higher order moments of crop yields distribution (see, *e.g.*, McCarl et al., 2008). One way of achieving this goal is to rely on the theoretical framework of Just and Pope's stochastic production function (Just and Pope, 1978).

This third chapter aims at estimating the effects of climate change on the European agriculture in terms of wheat and corn mean and variance yields, controlling for production prices. The estimated coefficients are then used to simulate the effects on agricultural yields of projected changes in precipitation and temperature, under different scenarios.

The content of this chapter makes three contributions to the analysis of climate change in the European Union. First, the effects of the weather on both the mean and the variance of two major crops, wheat and corn are assessed using statistical methods. Second, year-to-year fluctuation in prices and their potential impact on crop yields are incorporated in the study. The structural changes brought on by the 1999 CAP reform are accounted for. Hence, the response by farmers following the reduction in market support for prices after the reform can be examined. Third, this study covers a large part of western Europe and gives the panorama of both historical and potential forthcoming effects of the weather on agricultural yields.

The remainder of this chapter is organized as follows. In section 2, we describe the modelling framework and the empirical strategy used in the analysis. In section 3 we illustrate data and in section 4 we present the estimation results. Section 5 exposes projected yields under different climate scenarios. Section 6 concludes.

2 Modelling Framework and Estimation Procedure

To assess the effects of the weather and socio-economic variables on both the average and variability of crop yields in the European Union, a stochastic production function approach of the form suggested by Just and Pope (Just and Pope, 1978,9) is applied. This section first presents the modelling framework and then describes the empirical approached.

2.1 An Estimation by Maximum Likelihood

The basic idea of this framework is to define the production function as a sum of two components. The first term is deterministic and linked to the output level while the second term is linked to the variability of that output. The advantage of this approach is that it allows to estimate the impacts of an input variable, such as the weather, on both expected output and on its variance. In fact, these effects could be different. The general form of the Just and Pope production function for a given crop is:

$$y_i = f(\boldsymbol{X}_i, \beta) + u_i, \tag{3.1}$$

$$u_i = h(\boldsymbol{X}_i, \alpha)\varepsilon_i \tag{3.2}$$

where y_i, is crop yields of the i^{th} observation, with $i = 1, \ldots, n$, and $f(\cdot)$ is an average production function. The matrix $\boldsymbol{X}$ contains the explanatory variables (the weather, prices, irrigation, soil characteristics), and u is an error term with zero mean and variance $\sigma_u^2 = h(X, \alpha)^2$. The function $h(\cdot)$ for the error term accounts for heteroskedasticity. The vectors α and β are the unknown parameters to be estimated. In addition, we assume that ε_i is a random error normally distributed with zero mean and variance $\sigma_{\varepsilon_i}^2 = 1$.

In this framework, the effects of explanatory variables on mean yields and on the variance of yields are assumed not to be tied so that $\mathbb{E}(y) = f(\boldsymbol{X}, \beta)$ and $\mathbb{V}(y) = h(\boldsymbol{X}, \alpha)^2$. The effect of an input (*e.g.*, weather variable) can thus be different on mean yields and on yield variability.

The stochastic production function defined by eq. (3.1) can be estimated using a three-step estimation procedure involving feasible generalized least squares (FGLS) under heteroscedastic disturbances (as in Cabas et al., 2010). However, in the case of small samples, maximum likelihood estimators are more efficient and less biased than FGLS ones (Saha et al., 1997). We thus estimate the parameters of the regression in a single step by maximum likelihood (as in Chen et al., 2004), using the FGLS estimates as initial values for the optimization algorithm.

The estimation procedure encompasses three steps. The first one consists in regressing yields on the set of dependent variables using ordinary least squares. Residuals from this regression are an estimator of $h(\boldsymbol{X}, \alpha)\varepsilon$. They are used in the second step to estimate the marginal effects of dependent variables on the variance (Cabas et al., 2010). We assume that $h(\cdot)$ has an exponential form. Hence, we regress the logarithm of squared residuals on the set of explanatory variables. Predicted values of this second regression are used in a third step as weights in the regression by weighted least squares of yields on the set of independent variables. The estimates from this third step are the starting values used in the maximum likelihood estimation. Assuming that $\varepsilon_i \sim \mathcal{N}(0, 1)$, the log likelihood function reads as follows:

$$\ln L = -\frac{1}{2}\left[n\ln(2\pi) + \sum_{i=1}^{n} \ln\left(h(\boldsymbol{X}, \alpha)^2\right) + \sum_{i=1}^{n} \frac{(y_i - f(\boldsymbol{X}, \beta))^2}{h(\boldsymbol{X}, \alpha)^2}\right]. \tag{3.3}$$

The maximum likelihood estimates of α and β are obtained by maximizing eq. (3.3) with respect to α and β.

2.2 The Production Function Assumption

It is necessary to make an assumption on the production function $f(\cdot)$. It is common practice to assume a linear form. The matrix X from eq. (3.1) is split in sub-groups of variables: climate W, crop prices P, percentage of irrigated surface I, soil characteristics S.

Yields of crop $c \in \{m, w\}$, where m stands for for corn and w for wheat, in region r and in year t are modeled as follows:

$$\begin{aligned} y_{crt} = & \beta_{c1}\boldsymbol{W}_{crt} + \beta_{c2}P_{ct-1} + \beta_{c3}I_{crt} + \beta_{c4}S_{cr} + \\ & \beta_{c5}\text{CAP}_t^{1999} + \beta_{c6}\text{CAP}_t^{1999} \times P_{ct-1} + \mu_c + u_{crt}. \end{aligned} \tag{3.4}$$

We introduce a dummy variable, CAP_t, to reflect the effects of the 1999 Common Agricultural Policy reform. This variable takes the value 1 up to 1999 and zero afterwards. An interaction term between prices and the 1999 CAP reform dummy variable is also introduced in the equation, as we believe the effect of prices on production might differ after the market support for prices for cereals were reduced following the reform. Furthermore, prices are introduced in the model with a one period lag to account for their stickiness. We also add country fixed effects μ.[1] The set of weather variables W examines the effects of seasonal temperature, rainfall, and temperature deviation – measured as the spread between the maximum and the minimum observed temperature. Weather variables are disaggregated to enable their effects on yields to vary between seasons. The weather variables whose effects on either mean yields or yield variability are not significant are discarded from the model. As the model is used once it is estimated to assess the potential effects of climate change on yields, keeping variables with non-significant effects might bias the predictions. Finally, soil characteristics of each region are introduced to account for the heterogeneity in soil quality.

In the presence of spatial correlation, estimates might be biased and inconsistent (Miao et al., 2015; Auffhammer et al., 2013; Schlenker and Lobell, 2010). To overcome this pitfall we rely on $1,000$ bootstrap runs, randomly selecting observations[2] to estimate both coefficients and standard errors.

As the data generating process of corn and wheat yields may differ for northern and southern regions, the model described in eq. (3.4) is estimated for two subsets: one for northern regions and the other for southern ones. We use the $45°$ parallel north to separate northern and southern regions.[3]

[1]Fixed effects are introduced at the country level and not at the region level to avoid an overuse that can lead to estimators with inflated variability (Van Passel et al., 2016).

[2]In each run, we randomly select 80% of available observation and get rid of the 20% left.

[3]Using the 45° parallel north fairly separates the regions between the Mediterranean and the others ones, as displayed in Füssel et al. (2012, p. 27).

3 Data Sets and Empirical Specifications

We focus on the effects of weather variables on yields for two important grain crops, *i.e.*, wheat and corn. Our study covers 19 years of observations from 1991 to 2009 in 31 European regions for wheat producers and 25 for corn producers. The main information is collected from the Farm Accountancy Data Network. The dataset is complemented by regional registers or surveys that provide information on spatial location variables. eq. (3.4) is estimated using data gathered from five different databases.

3.1 Production Data and Definition of the Agricultural Variables

First, we use data from the Farm Accountancy Data Network[4] (FADN) apportioned down to NUTS-3 geographic level for statistical anonymity. We only focus on representative farms whose main stated activity is crop growing, and collect three variables: production, cultivated area, and yields. The values of each of these variables are not necessarily provided for the entire period. Hence, we discarded regions for which less than 15 observations were available.[5] The number of NUTS-3 regions used in this chapter as well as the number of observation are reported by country in table 3.1. As previously mentioned, we use the $45°$ parallel North to differentiate northern and southern regions. Regions with a centroid above this parallel are included in the northern sample while the other regions are included in the southern sample.

Information at the average level for each region is reported in fig. 3.1 for production, area and yields for both crops. The subplots on the left describe the wheat case while those on the right side depict the corn case. tables 3.2 and 3.3 offer a complementary view on the description of the data, for the sample used to analyse wheat and corn yields, respectively. Descriptive statistics are reported for the entire period covered, from 1991 to 2009, as well as for two subsets, before and after the 1999 CAP reform, *i.e.*, from 1991 to 1999, and from 2000 to 2009, respectively. For each of these three different setups, descriptive statistics are also reported for northern and southern regions, separately.

[4]The FADN database is publicly available at `http://ec.europa.eu/agriculture/rica/database/consult_std_reports_en.cfm`.

[5]This concerns only five regions in the sample.

Table 3.1: Number of NUTS-3 Regions and Observation by Country and Location

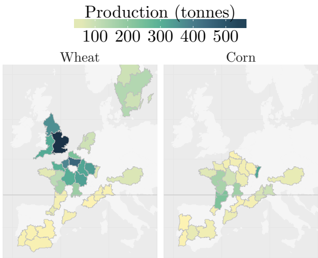
	Wheat				Corn			
	North		South		North		South	
	NUTS-3	Obs.	NUTS-3	Obs.	NUTS-3	Obs.	NUTS-3	Obs.
Austria	1	14	-	-	1	14	-	-
France	15	234	15	36	16	234	16	54
Italy	2	36	-	-	2	36	-	-
Netherlands	1	18	-	-	-	-	-	-
Portugal	-	-	1	18	-	-	2	36
Spain	-	-	6	107	-	-	4	72
Sweden	2	28	-	-	-	-	-	-
United Kingdom	3	54	-	-	-	-	-	-
Total	24	384	22	161	19	284	22	162

Notes: This table gives the number of observations in the four different datasets used in this analysis (wheat yields in northern regions, wheat yields in southern regions, corn yields in northern region, and corn yields in southern regions). The figures are aggregated at the country level here. Observations for the datasets on wheat yields are reported on the left while observations for the datasets on corn yields are reported on the right. Each dataset is also split between north and south regions. Regions whose centroid is higher than 45° are considered on the north while the others are considered on the south. The columns untitled "NUTS-3" give the number of NUTS-3 regions for each country in the datasets and the columns untitled "Obs." report the number of observation by country.

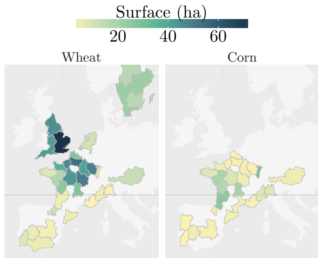
We observe major differences across northern and southern regions. Levels of all agricultural variables are higher in northern regions than in the southern ones. Remarkable difference is found for average yields. The average value of wheat yields in the north is about 70 quintals per hectare which is twice larger than the average value of yields in the south. For corn, a distinction between northern and southern regions is also observed, with the former being more productive than the latter. Even if both production and surface are almost twice higher in northern regions, the average value of corn yields is about the same in both northern and southern regions, and equals about 86 quintals per hectare. (table 3.3). It is noteworthy that wheat yields remained almost unchanged after the 1999 CAP reform, with a slight increase in both production and surface. On the other hand, corn yields in southern Europe improved substantially and have closed the gap as compared to yields in northern Europe.

The FAO offers data on nominal producer prices, expressed in USD per ton,[6] at the country level. We divide this variable by a 2004–2006 producer price index given for each type of crop. This yields a variable of real prices. As shown in fig. 3.2, wheat and corn production prices decline up to 2001, then start increasing. We also observe a notable difference between prices observed in northern and southern regions, production prices being relatively higher in southern regions.

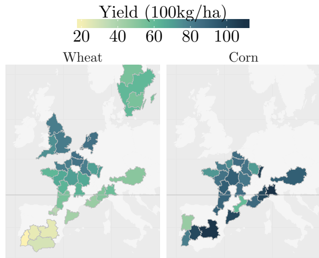
[6]We stick to US Dollars rather than converting prices in Euros, as the former is the currency used in the global agricultural market.



(a) Average Production



(b) Average Surface



(c) Average Yields

Notes: The vertical grey line represents the 45° parallel north used to separate northern and southern regions.

FIGURE 3.1: Agricultural Production of Wheat and Corn in Western Europe

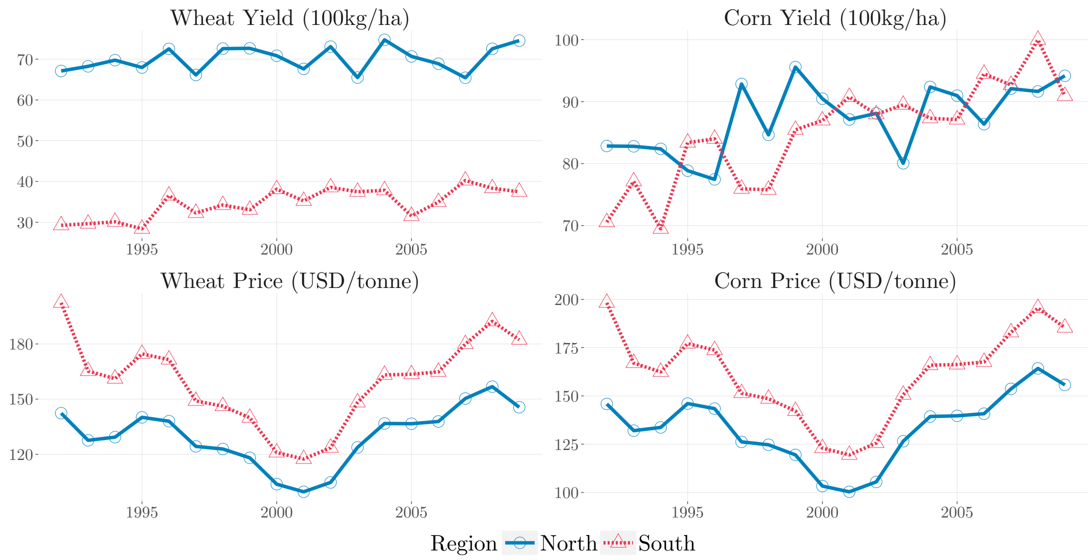


FIGURE 3.2: Evolution of Yields and Prices

3.2 Environment Data and Spatial Location of the Farm Variables

Locating farms within its spatial environment is very important to understand differences in production decisions. The environment affects agricultural production, *via* water availability, soil composition, or the weather.

Previous studies point out the importance of irrigation. In fact, the effect of climate change on agriculture might be different for irrigated and rain-fed farms (Schlenker et al., 2005). This information is not given in the Public FADN database. Hence, we use the share of irrigable agricultural area by region as a proxy (as in Polsky and Easterling III, 2001; Gbetibouo and Hassan, 2005; Barnwal and Kotani, 2013). We divide the total irrigable area by the utilized agricultural area obtained from Eurostat[7] to get the share of irrigable agricultural area.[8] Table 3.2 and table 3.3 show that the share of irrigable area is higher in the south than it is in the north, although the standard deviation is higher in the north.

The geographical location of the farm influences the type of crops that are cultivated, and also affects yields. Increased latitude might be harmful to crop production, as regions in higher latitude are less exposed to solar radiation, which are determinant of yields according to agronomic models. On the other hand, regions closer to the equator are subject to hotter climate that may have detrimental effects on yields. Longitude should also be considered. As pointed-out by Vanschoenwinkel et al. (2016), Western and Eastern Europe do not respond to climate variation in the same way.

The FADN data does not include any information on physical properties of the soil. The characteristics of soil play an important role in the crop's ability to extract water and nutrients. Soil texture or the proportions of different-sized mineral particles that soil contains must provide a good environment for plant growth. Hence we take into account the soil's composition using different measures. Soil quality heterogeneity is addressed using a worldwide $21,600 \times 43,200$ raster database of soil characteristics from the Harmonized World Soil Database (Batjes et al., 2008). We compute NUTS-3 averages for the four measures relative to the texture of topsoil: gravel content by volume; sand , silt, and clay fraction as a percentage of weight. More details on the values are given on table 3.2 and on table 3.3.

3.3 Weather Data and Definition of the Variables

The key climatic variables that impact crops yields are surface temperature, and level of rainfall. In this study we adopt information provided in a global climate model, MRI-CGCM3, which has been developed at the Meteorological Research Institute (MRI). This framework integrates a global dataset built on a $1.125° \times 1.12148°$ longitude latitude grid since 1850. Daily precipitation and levels of temperature are available. We select data on average temperature, total rainfall and temperature deviations. Temperature deviations are computed as the difference between the maximum and the minimum temperatures, within a day.

[7] Data on irrigated areas is available at http://ec.europa.eu/eurostat/web/products-datasets/-/ef_lu_ofirrig.

[8] The information on irrigable area provided by Eurostat is given only in some NUTS-3 regions an only every two or three years, so we estimate the missing values in the following way: we keep regions where at least four observations are given, and impute the missing values by means of B-Splines.

Our aim is to define weather variables at the regional dimension. Hence in a first step we aggregate data at the NUTS-3 level. In the calculus we take into account the relative importance of the cells of the grid in the region by weighting each information by the share of the cell in the region. The second step is to change the time dimension to match with previous data collected from the FADN data set. We do not define annual climate variables. In reality, crop development, *i.e.*, the time from planting to flowering and/or maturity, which takes place in one year is correlated with temperature and precipitation levels. Climatic factors can promote or inhibit plant growth and development. Hence, daily data of each weather measure are averaged by seasons. For one year, we distinguish four time information: (i) Winter, from December to February; (ii) Spring, from March to May; (iii) Summer, from June to August; and (iv) Fall, from September to November. These different periods of time define different steps in the development of crops. The first one defines (i) the seeding season for the initial development, (ii) the vegetative growth stage for the stem extension, and (iii) the generative growth stage for the ripening and harvesting of the plant.

4 Estimation Results

In this section, we present the estimates for the average crop yields production function, and for the crop yield variability function.

The coefficients of the production function, estimated by maximum likelihood, and their associated standard errors are reported in table 3.4.[9] The first four columns report the effects on mean yields while the next four give the effects on the variance of yields.

4.1 Wheat Yields

Mean wheat and variance yields are affected by seasonal temperatures. The effects of temperature on wheat yields are significant only in summer, for northern regions. Any additional degree Celsius in summer is harmful to mean yields though it reduces the variance of yields. Temperature variables of other seasons were removed from the estimation since the effect of these variables on both mean yields and the variance of yields were found not significant. Temperature deviation plays a more important role in explaining variations of mean yields and the variance of yields. Temperature deviation in summer negatively impact mean wheat yields in the north and increases its variance. In fall, the opposite effect is observed, with a positive impact on mean yields

[9]Country-specific coefficients are omitted for clarity purposes; they are available upon request.

Table 3.2: Descriptive Statistics (Mean and Std) for Wheat Datasets

		Whole Period (1991-2009)			Before CAP Reform (1991-2000)			After CAP Reform 2001-2009		
Variable	Unit	All	North	South	All	North	South	All	North	South
Production variables										
Yield	100 kg per ha	59.63	70.1	34.65	58.6	69.85	32.43	60.61	70.33	36.84
		(20.37)	(11.95)	(13.33)	(21.09)	(11.67)	(13.48)	(19.64)	(12.23)	(12.9)
Wheat production	$100kg	1650.24	2268.4	175.87	1536.7	2130.56	155.96	1758.49	2397.88	195.54
		(1675.85)	(1637.37)	(163.77)	(1582.91)	(1549.67)	(142.3)	(1755.9)	(1709.46)	(181.26)
Wheat surface	ha	23.03	30.53	5.16	21.59	28.7	5.05	24.42	32.24	5.28
		(20.39)	(19.81)	(4.27)	(19.53)	(19.23)	(4.26)	(21.12)	(20.24)	(4.3)
Wheat prices	USD/100kg	138.44	129.74	159.18	136.51	126.88	158.89	140.28	132.43	159.45
		(29.63)	(24.14)	(31.23)	(29.39)	(22.07)	(32.09)	(29.79)	(25.7)	(30.54)
Environment variables and spatial location of the farm										
Irrigable area	%	12.83	10.99	17.21	12.44	10.41	17.17	13.19	11.53	17.25
		(14.12)	(15.95)	(6.44)	(14.03)	(15.7)	(7.14)	(14.21)	(16.19)	(5.71)
Latitude	o	47	49.49	41.05	46.83	49.31	41.05	47.16	49.66	41.06
		(5.01)	(3.49)	(2.38)	(4.85)	(3.26)	(2.4)	(5.16)	(3.69)	(2.38)
Longitude	o	2.08	3.82	−2.08	1.8	3.47	−2.1	2.34	4.14	−2.05
		(5.48)	(5.08)	(3.97)	(5.22)	(4.78)	(3.99)	(5.71)	(5.33)	(3.98)
Gravel Content	%vol.	8.84	7.84	11.23	8.8	7.76	11.22	8.88	7.91	11.24
		(2.23)	(1.45)	(1.93)	(2.24)	(1.41)	(1.94)	(2.23)	(1.5)	(1.93)
Sand Fraction	%wt.	43.73	43.7	43.8	43.67	43.6	43.83	43.78	43.79	43.76
		(5.32)	(4.19)	(7.36)	(5.34)	(4.19)	(7.39)	(5.3)	(4.19)	(7.37)
Silt Fraction	%wt.	32.74	32.59	33.1	32.76	32.62	33.08	32.73	32.57	33.12
		(3.8)	(3.33)	(4.73)	(3.82)	(3.35)	(4.75)	(3.78)	(3.32)	(4.74)
Clay Fraction	%wt.	22.03	21.88	22.38	22.11	22.01	22.36	21.94	21.76	22.39
		(3.15)	(2.98)	(3.51)	(3.12)	(2.93)	(3.53)	(3.18)	(3.02)	(3.51)
Weather variables										
Temp. (winter)	^oC	4.62	3.7	6.82	4.52	3.61	6.62	4.72	3.78	7.02
		(3.06)	(3)	(1.85)	(2.98)	(2.91)	(1.9)	(3.14)	(3.09)	(1.8)
Temp. (spring)	^oC	9.15	8.21	11.38	8.99	8.04	11.18	9.3	8.37	11.57
		(2.64)	(2.34)	(1.89)	(2.56)	(2.18)	(1.95)	(2.72)	(2.47)	(1.81)
Temp. (summer)	^oC	17.6	16.72	19.7	17.74	16.94	19.62	17.46	16.52	19.77
		(2.2)	(1.62)	(1.99)	(2.13)	(1.68)	(1.87)	(2.27)	(1.54)	(2.11)
Temp. (fall)	^oC	10.39	9.36	12.85	10.26	9.33	12.4	10.52	9.39	13.3
		(2.79)	(2.36)	(2.15)	(2.44)	(2.03)	(1.9)	(3.1)	(2.63)	(2.3)
Temp. Dev. (winter)	^oC	4.49	4.22	5.14	4.5	4.23	5.11	4.49	4.21	5.17
		(0.98)	(0.93)	(0.76)	(0.96)	(0.93)	(0.72)	(0.99)	(0.93)	(0.8)
Temp. Dev. (spring)	^oC	7.09	6.73	7.97	7.09	6.72	7.93	7.1	6.73	8
		(1.36)	(1.27)	(1.16)	(1.36)	(1.27)	(1.17)	(1.37)	(1.28)	(1.16)
Temp. Dev. (summer)	^oC	7.77	7.41	8.64	7.8	7.47	8.56	7.75	7.35	8.73
		(1.52)	(1.43)	(1.38)	(1.55)	(1.51)	(1.36)	(1.5)	(1.35)	(1.41)
Temp. Dev. (fall)	^oC	5.32	4.93	6.26	5.2	4.86	5.97	5.44	4.99	6.54
		(1.21)	(1.04)	(1.05)	(1.08)	(0.97)	(0.93)	(1.3)	(1.1)	(1.09)
Precip. (winter)	m	8.1	9.24	5.39	7.64	8.72	5.14	8.54	9.73	5.64
		(3.16)	(2.63)	(2.65)	(2.95)	(2.52)	(2.29)	(3.3)	(2.64)	(2.96)
Precip. (spring)	m	6.68	7.06	5.77	6.37	6.73	5.52	6.97	7.37	6.01
		(1.99)	(1.79)	(2.14)	(1.97)	(1.78)	(2.15)	(1.96)	(1.75)	(2.11)
Precip. (summer)	m	6.35	6.47	6.05	6.55	6.58	6.47	6.15	6.37	5.62
		(2.72)	(2.2)	(3.66)	(2.83)	(2.17)	(3.98)	(2.6)	(2.23)	(3.29)
Precip. (fall)	m	8.75	9.39	7.22	9.59	10.22	8.13	7.94	8.6	6.32
		(2.79)	(2.54)	(2.75)	(2.78)	(2.5)	(2.86)	(2.55)	(2.34)	(2.32)
No Observations		545	384	161	266	186	80	279	198	81

Notes: Descriptive statistics (mean and standard error in parenthesis) for all regions, northern regions only and souther regions only, before and after the 1999 Common Agricultural Policy reform.Prices are expressed in constant 2005 USD per 100kg.

following a unit spread increase between maximum and minimum daily temperature, and a diminution of wheat the variance of yields, although the impact on variance is not significant at the 5% level. In winter, the sign of the effect of temperature deviation on mean yields is opposed for northern and southern regions, but the coefficients are not significant. However, for both northern and southern regions, an increase in winter temperature deviation significantly reduces the variance of yields. Finally, precipitation also alter mean an the variance of yields. We allowed for a quadratic effect, but it was rejected by the data for all seasons. Precipitation in spring, summer, and winter have a negative impact on wheat yields in the north. In the south, while the

TABLE 3.3: Descriptive Statistics (Mean and Std) for Corn Datasets

		Whole Period (1991-2009)			Before CAP Reform (1991-2000)			After CAP Reform 2001-2009		
Variable	Unit	All	North	South	All	North	South	All	North	South
Production variables										
Yield	100 kg per ha	86.48	87.34	84.96	82.97	85.42	78.74	89.92	89.21	91.19
		(18.05)	(13.78)	(23.73)	(17.7)	(13.71)	(22.51)	(17.77)	(13.65)	(23.42)
Corn production	$100kg	674.1	807.96	439.43	604.01	728.45	388.92	742.95	885.26	489.94
		(812.08)	(852.06)	(677.94)	(777.61)	(806.21)	(677.93)	(840.61)	(890.38)	(678.37)
Corn surface	ha	7.36	8.77	4.88	6.74	8.06	4.47	7.96	9.46	5.3
		(8.28)	(8.43)	(7.42)	(8.04)	(8.13)	(7.39)	(8.5)	(8.69)	(7.48)
Corn prices	USD/100kg	143.43	133.27	161.26	141.31	130.26	160.4	145.53	136.19	162.12
		(29.39)	(21.51)	(32.73)	(28.84)	(18.7)	(33.12)	(29.83)	(23.63)	(32.52)
Environment variables and spatial location of the farm										
Irrigable area	%	14.89	12.67	18.79	15.02	12.18	19.92	14.77	13.15	17.65
		(15.27)	(17.63)	(8.62)	(15.46)	(17.25)	(10.12)	(15.11)	(18.05)	(6.67)
Latitude	^{o}	45.54	47.8	41.58	45.52	47.8	41.58	45.56	47.8	41.58
		(3.47)	(1.53)	(2.12)	(3.49)	(1.54)	(2.12)	(3.47)	(1.52)	(2.12)
Longitude	^{o}	1.7	3.68	−1.77	1.59	3.53	−1.77	1.81	3.83	−1.77
		(5.06)	(4.14)	(4.66)	(4.95)	(3.98)	(4.68)	(5.18)	(4.29)	(4.68)
Gravel Content	%vol.	9.04	7.9	11.05	9.04	7.87	11.05	9.05	7.92	11.05
		(2.09)	(1.09)	(1.89)	(2.1)	(1.09)	(1.9)	(2.08)	(1.1)	(1.9)
Sand Fraction	%wt.	43.97	42.88	45.88	43.97	42.86	45.88	43.97	42.89	45.88
		(5.24)	(3.22)	(7.19)	(5.27)	(3.25)	(7.22)	(5.22)	(3.21)	(7.22)
Silt Fraction	%wt.	33.04	33.55	32.14	33.01	33.52	32.14	33.06	33.58	32.14
		(3.73)	(3)	(4.62)	(3.74)	(3.02)	(4.63)	(3.72)	(3)	(4.63)
Clay Fraction	%wt.	22.09	22.57	21.25	22.12	22.62	21.25	22.07	22.53	21.25
		(2.9)	(2.63)	(3.15)	(2.9)	(2.63)	(3.16)	(2.9)	(2.65)	(3.16)
Weather variables										
Temp. (winter)	^oC	5.1	4.21	6.66	4.89	3.97	6.47	5.31	4.44	6.85
		(2.53)	(2.51)	(1.67)	(2.59)	(2.56)	(1.73)	(2.46)	(2.44)	(1.61)
Temp. (spring)	^oC	9.72	8.91	11.15	9.47	8.61	10.95	9.97	9.2	11.34
		(1.95)	(1.63)	(1.64)	(1.97)	(1.58)	(1.69)	(1.91)	(1.63)	(1.58)
Temp. (summer)	^oC	18.13	17.37	19.46	18.24	17.57	19.4	18.01	17.17	19.51
		(1.6)	(1.05)	(1.52)	(1.51)	(1.09)	(1.45)	(1.67)	(0.97)	(1.6)
Temp. (fall)	^oC	10.87	9.86	12.64	10.66	9.75	12.24	11.09	9.98	13.05
		(2.35)	(1.96)	(1.87)	(2.04)	(1.69)	(1.59)	(2.6)	(2.2)	(2.03)
Temp. Dev. (winter)	^oC	4.62	4.37	5.05	4.63	4.41	5.01	4.6	4.33	5.09
		(0.91)	(0.9)	(0.76)	(0.88)	(0.89)	(0.73)	(0.94)	(0.91)	(0.79)
Temp. Dev. (spring)	^oC	7.34	7.06	7.83	7.34	7.06	7.81	7.34	7.05	7.85
		(1.21)	(1.15)	(1.17)	(1.2)	(1.13)	(1.18)	(1.23)	(1.17)	(1.17)
Temp. Dev. (summer)	^oC	8.13	7.9	8.54	8.15	7.97	8.45	8.12	7.83	8.63
		(1.34)	(1.28)	(1.34)	(1.36)	(1.35)	(1.32)	(1.31)	(1.2)	(1.35)
Temp. Dev. (fall)	^oC	5.59	5.27	6.16	5.44	5.18	5.89	5.75	5.36	6.43
		(1.08)	(0.96)	(1.06)	(0.97)	(0.88)	(0.95)	(1.16)	(1.02)	(1.09)
Precip. (winter)	m	8.26	9.31	6.42	7.76	8.68	6.17	8.75	9.92	6.68
		(3.33)	(2.68)	(3.56)	(3.16)	(2.6)	(3.41)	(3.43)	(2.63)	(3.71)
Precip. (spring)	m	6.98	7.37	6.29	6.62	6.98	6.01	7.33	7.76	6.57
		(2.01)	(1.78)	(2.2)	(2.05)	(1.84)	(2.27)	(1.91)	(1.64)	(2.11)
Precip. (summer)	m	6.49	6.73	6.07	6.74	6.87	6.5	6.25	6.59	5.64
		(2.67)	(2.36)	(3.1)	(2.75)	(2.3)	(3.39)	(2.57)	(2.42)	(2.74)
Precip. (fall)	m	9.2	9.72	8.28	10.23	10.77	9.28	8.19	8.7	7.27
		(3.02)	(2.56)	(3.52)	(3.07)	(2.41)	(3.79)	(2.61)	(2.27)	(2.92)
No Observations		446	284	162	221	140	81	225	144	81

Notes: Descriptive statistics (mean and standard error in parenthesis) for all regions, northern regions only and souther regions only, before and after the 1999 Common Agricultural Policy reform.Prices are expressed in constant 2005 USD per 100kg.

effect of an increase in precipitation in summer is of the same sign as in northern regions, *i.e.*, negative, it is positive in winter, although only significant at the 10% level.

Irrigable surface, used as a proxy for irrigation has a positive impact on mean yields, but is only significant in the north of Europe.

We introduce the effect of an important CAP reform over the studied period, the Agenda 2000. The aim of this reform was to further pursue the 1992 reform of the CAP and press ahead with the transition to world market prices, particularly through a substantial drop in the common support prices for cereals. Hence, regarding the effects of price in our analysis, a distinction between two periods needs to be done: before the 1999 reform of the PAC, and after. In the former period, the dummy variable takes zero values. Since we introduced an interaction term between prices and the dummy variable, the effect of a unit increase in prices reads as the sum of the coefficients of the price variable and the interaction between the dummy and price variables, *i.e.*, $\beta_{c2} + \beta_{c6}$ in eq. (3.4). After 1999, it reads as the coefficient associated with the price variable only, *i.e.*, β_{c2} in eq. (3.4). The results of the regressions show that prices before the 1999 CAP reform played a positive though not significant role in explaining the variations of mean yields of wheat in northern regions, *i.e.*, regions in which production in relatively higher. After the CAP reform, the effect remains positive and becomes significant. For southern regions, prices have a significant and positive effect on wheat the variance of yields. We note that the effect of prices are lower after the reform. This result is linked to the fact that changing policy might reduce the incentive for intensive cultivation and therefore lower the rate of yields gains. In addition, changing environmental policies included in Agenda 2000 restricted the use of fertilizer application and may have limited yields growth.

4.2 Corn Yields

Seasonal weather variables impact both mean yields and the variance of yields. Temperature in winter only impacts yields in northern regions: a unit increase is harmful to mean yields and also increases the variance of yields. In spring, temperature does not significantly affect corn yields in the north of Europe. However, in the south, there is a hill-shape relationship between temperature and yields. There is a threshold above which any additional degree Celsius becomes harmful to corn yields. The value of this threshold is $9.24°$C, which is comprised in the range of observed values, a bit lower than the observed average. Temperature in summer negatively affects corn mean yields in the south. In the north, the effect on the mean is not significant, but an increase in temperature reduces the variance of corn yields. In fall, there is a quadratic effect of temperature on corn yields. Above a threshold of $12.30°$C, any additional temperature increase leads to a deterioration of mean yields for regions in the north of Europe. The value of this threshold is comprised in the range of observed values of fall temperatures, a bit higher than the average.

Temperature deviations mainly positively affect corn yields in the south, except for fall, where the coefficient is negative but not statistically different from zero. The impact of an increase in the spread between the maximum and the minimum daily temperature on the variance of corn yields is only significant in fall, for the south of Europe, and leads to a rise in this variance.

All precipitation variables were rejected by the model, at the exception of precipitation in fall, for southern regions only. In that particular case, an increase in total rainfall leads to an increase in the variance of yields.

Just like for wheat, irrigation surface has a positive effect on mean corn yields in the north of Europe. For region in the south of Europe, the share of irrigable areas only impact the variance of corn yields, negatively.

Contrary to the regressions for wheat, the dummy variable reflecting the CAP reform is rejected by the model. The interaction term between the dummy and prices is also not significant. Looking at prices alone, we see that they are positively linked to corn yields in the north of Europe; their effects in the south are not statistically different from zero.

5 Scenarios

Impacts of several climate change scenarios on crops yields are assessed in this study. These scenarios are conducted over the 2010–2100 period. Four Representative Concentration Pathways (RCPs) adopted by the IPCC for its fifth Assessment Reports in 2014 are used in our scenario exercise: RCPs 2.6, RCP4.5, RCP 6.0 and RCP 8.5. These pathways depict different greenhouse gas concentration trajectories from the most optimistic to the most pessimistic. The first three, *i.e.*, the RCPs 2.6, 4.5 and 6.0 are characterized by increasing greenhouse gas concentrations with a peak around 2030, 2040, and 2060, respectively, followed by a slow decline. The last scenario, the RCP 8.5, is less optimistic in terms of emissions and leads to a rapidly increasing concentration over the whole century.[10] Data come from the same source as the historical weather variables (see section 3.3).

Before implementing scenarios, we need to define projections levels for all exogenous variables. All variables except weather ones are set to their historical average from 1991 to 2009. The weather variables vary according to the climate scenario envisaged. Furthermore, for each of the four scenarios, two different time horizons are examined:

[10]The appendix B displays descriptive statistics of weather variables for each scenario as well as historical values.

TABLE 3.4: Determinants of Wheat and Corn Yield (Maximum Likelihood)

	Mean Yield				Yield Variance			
	Wheat		Corn		Wheat		Corn	
	(North)	(South)	(North)	(South)	(North)	(South)	(North)	(South)
Price Lagged	0.082^{***}	-0.016	0.115^{***}	-0.030	$-0.009^{\cdot}$	0.001	-0.004	0.024^{***}
	(0.017)	(0.027)	(0.033)	(0.067)	(0.006)	(0.007)	(0.007)	(0.010)
Irrigable area	0.169^{***}	0.219	0.701^{***}	$0.555^{\cdot}$	0.010	0.082^{*}	0.007	-0.112^{**}
	(0.049)	(0.204)	(0.134)	(0.396)	(0.020)	(0.051)	(0.026)	(0.052)
D^{1999}	5.287^{**}	-7.212	-1.052	9.652	$-1.321^{\cdot}$	1.384	0.448	1.473
	(2.864)	(6.932)	(6.951)	(13.397)	(0.950)	(1.399)	(1.650)	(1.382)
D^{1999} x Price Lagged	-0.055^{***}	0.025	-0.040	$-0.136^{\cdot}$	0.012^{*}	$-0.012^{\cdot}$	-0.0002	-0.003
	(0.021)	(0.040)	(0.049)	(0.083)	(0.007)	(0.009)	(0.012)	(0.008)
Latitude	1.691^{**}	399.408^{***}	$-1.114^{\cdot}$	60.099^{***}	0.048	-25.472	$-0.212^{\cdot}$	-0.409
	(0.660)	(59.563)	(0.775)	(17.418)	(0.139)	(21.382)	(0.148)	(2.684)
Longitude	2.171^{***}	-39.432^{***}	0.207	$3.639^{\cdot}$	$-0.150^{\cdot}$	1.952	0.076	$0.549^{\cdot}$
	(0.400)	(5.890)	(0.692)	(2.963)	(0.121)	(2.192)	(0.113)	(0.421)
Gravel Content	0.361	52.770^{***}	1.718^{**}	-59.167^{***}	0.047	-2.756	-0.008	0.522
	(0.540)	(8.180)	(0.712)	(9.479)	(0.127)	(3.014)	(0.140)	(1.477)
Sand Fraction	-0.814^{**}	$-2,315.835^{***}$	1.024	-812.160^{***}	$0.163^{\cdot}$	152.273	-0.168	8.614
	(0.378)	(346.363)	(1.143)	(175.207)	(0.112)	(124.099)	(0.128)	(26.238)
Silt Fraction	0.539	$-2,554.501^{***}$	0.447	-847.371^{***}	$0.200^{\cdot}$	167.941	-0.151	8.946
	(0.560)	(382.113)	(1.319)	(183.417)	(0.145)	(136.928)	(0.162)	(27.508)
Clay Fraction	-0.923^{*}	$-1,743.921^{***}$	0.784	-672.498^{***}	0.109	114.776	-0.032	6.817
	(0.481)	(260.636)	(1.170)	(143.252)	(0.125)	(93.370)	(0.142)	(21.487)
Temp. (winter)			-2.539^{***}				0.425^{***}	
			(0.657)				(0.145)	
Temp. (spring)				20.649^{*}				2.320^{*}
				(9.739)				(1.351)
Temp. (spring) sq.				-1.117^{**}				$-0.084^{\cdot}$
				(0.423)				(0.061)
Temp. (summer)	-1.062^{**}		0.279	-2.265^{**}	-0.463^{***}		-0.381^{***}	0.082
	(0.491)		(0.752)	(1.314)	(0.111)		(0.114)	(0.188)
Temp. (fall)			7.193^{**}				$0.826^{\cdot}$	
			(3.000)				(0.562)	
Temp. (fall) sq.			-0.292^{**}				-0.053^{**}	
			(0.140)				(0.027)	
Temp. Dev. (winter)	-1.140	2.825			-0.621^{***}	-1.826^{***}		
	(1.108)	(2.394)			(0.230)	(0.411)		
Temp. Dev. (spring)				7.610^{***}				-0.150
				(2.535)				(0.408)
Temp. Dev. (summer)	-3.096^{***}			6.164^{***}	0.764^{***}			-0.130
	(0.905)			(2.006)	(0.208)			(0.298)
Temp. Dev. (fall)	2.423^{***}		-3.094^{**}	-3.473	-0.216		-0.169	1.205^{***}
	(0.843)		(1.506)	(3.575)	(0.262)		(0.229)	(0.507)
Precip. (winter)	-0.315^{**}	$0.783^{\cdot}$			-0.022	-0.240^{***}		
	(0.150)	(0.566)			(0.042)	(0.070)		
Precip. (spring)	-0.612^{**}				-0.146^{**}			
	(0.219)				(0.071)			
Precip. (summer)	-0.654^{***}	-0.678^{**}			0.128^{*}	0.031		
	(0.239)	(0.345)			(0.075)	(0.072)		
Precip. (fall)				-0.610				0.174^{**}
				(0.538)				(0.077)
Observations	384	161	284	162	384	161	284	162

Notes: Dot (·), asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10%, 5%, 1% and 0.1%, respectively.
Standard errors are in parentheses below the parameter estimates.

we refer to the short-run as the period ranging from 2009 to 2050; and to the long-run as the period ranging from 2051 to the end of the 21st century.

Under each scenario, average temperature rises with time. In addition, the later the projection of the peak for greenhouse gas concentration, the higher the average temperature.

We compare yields predicted by our models using observed weather data from 1991 to 2009, to those predicted under different scenarios. We proceed as follows. In each period, yearly yields are predicted by region for every bootstrap runs,[11] and then averaged, still by region, over the whole period. It is then also possible to compute the percentage change from the baseline to the projected scenario.

All variables except weather ones are kept at their mean value of the baseline period, *i.e.*, the period ranging from 1991 to 2009. Our projections do not account for any possible technological changes that are likely to occur, and should therefore not be viewed as a forecasting exercise.

The evolution of annual wheat and corn yields up to 2100 are plotted for each scenario in figs. 3.3 and 3.4. Results at the European scale of the percent change in yields of both wheat and corn under each scenario are reported in table 3.5, while figs. 3.5 and 3.6 show the spatial variability of projected changes.

On average, our scenarios exhibit small gains in terms of annual wheat yields, at the European scale. At a finer scale, results are more mitigated and heterogeneous changes in yields are found. In the north, gains are relatively small, close to zero, and tend to decrease in the long run. In the worst-case scenario, the RCP 8.5, annual wheat yields fall after the middle of the 21st century. Some regions, mainly eastern ones display losses under the tested climate scenarios. Gains in average yields are becoming lower with time, ranging from $+0.95\%$ in the short run for the RCP 6.0 scenario to even become negative in the long-run in the case of the doom-and-gloom RCP 8.5 scenario, with a loss of 1.74%. Results are more encouraging for regions in the south of Europe, where annual wheat yields would increase under each climate scenario envisaged. In addition, these gains are becoming even larger in the long-run, reaching $+6\%$ compared to annual yields obtained in the benchmark period. This result can be explained due to rising precipitation in winter under each scenario coupled with decreasing total rainfall in summer, which are both favourable conditions for wheat yields, according to the estimation results. However, the gains in average annual yields are associated with relatively large variance.

Results for corn yields also show spatio-temporal disparities. In the north, corn yields would globally increase in the short-run, ranging from $+1.04\%$ under the most optimistic scenario, the RCP 2.6, to $+0.62\%$ under the most pessimistic one, the RCP 8.5. In the long-run, however, climate conditions envisaged within the scenarios are not as hopeful. In fig. 3.4, we observe a positive trend for corn yields up to a peak whose date differs depending on the scenario. After this peak, corn yields in northern Europe tend

[11] Recall that the estimates of each model rely on $1,000$ bootstrap runs.

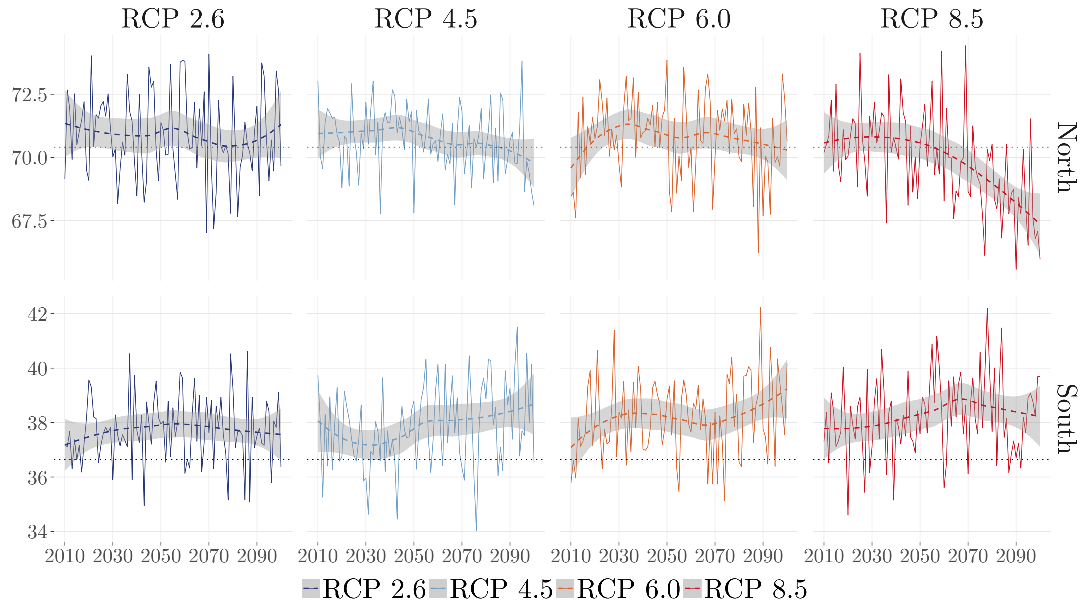
to gradually decrease. Even if corn yields under the RCPs 2.6 scenario remain close to their historical average of 1991–2009, they end-up below that average at the end of the century. Moreover, under the remaining scenarios, the RCPs 4.5, 6.0 and 8.5, projected climate values are such that corn yields substantially decrease in the long run to reach up to an average decline of -2.65% under the RCP 8.5 scenario. Results for southern regions are even more alarmist. In fact, with the exception of the optimistic RCP 2.6 scenario, where average annual corn yields would be small gains ($+0.58\%$), every other scenario leads to a drop in annual corn yields. However, in the short-run, those losses are close to zero. But in the long-run, the drop in yearly annual corn yields are more substantial, ranging from -4.40% in average under the most optimistic RCP 2.6 scenario to -19.88% in the case of the pessimistic RCP 8.5 scenario.

All in all, our scenarios exhibit a clear distinction between northern and southern regions. This distinction is also found in Van Passel et al. (2016), which projects the sensitivity of European farms to climate, looking at how land value reacts to a changing climate. They find changes in land value ranging from $+5$ to -32% by 2100 depending on the climate scenario. They predict farms in Southern Europe to be particularly sensitive, suffering losses of -5% to -9% per degree Celsius. Our results for projected corn yields are similar in terms of geographical effects. We find opposite effects for wheat yields. But our analysis, contrary to the Ricardian model used in Van Passel et al. (2016), focuses on a specific crop and thus does not incorporate the possibility for the farmer to switch crop if the weather conditions become too harmful. However, we find regional differences between western and eastern regions as in Vanschoenwinkel et al. (2016), although our sample includes less regions in eastern Europe.

6 Conclusion

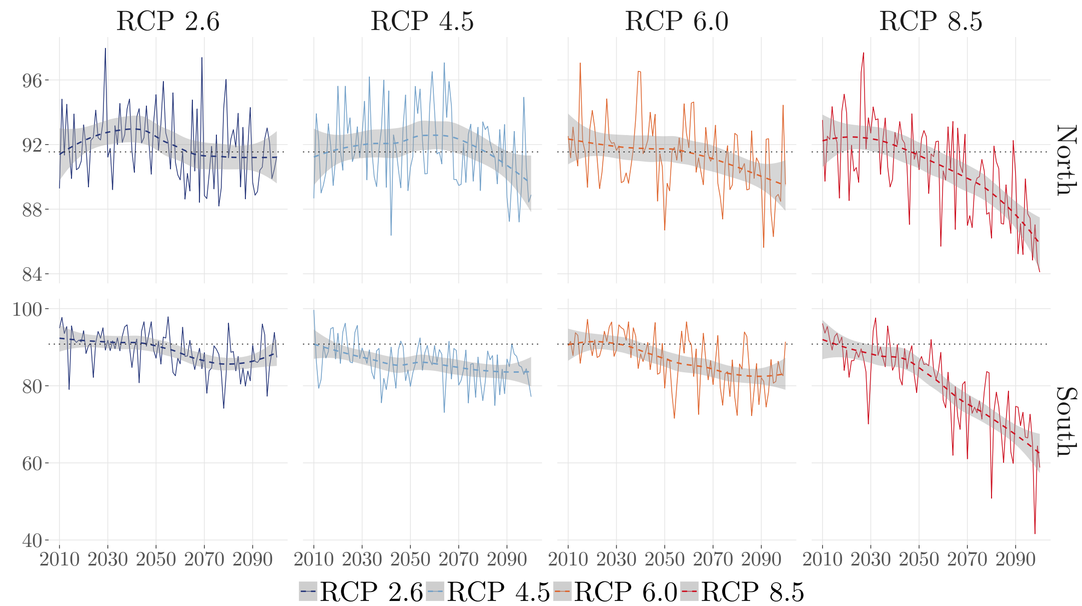
This chapter presents an assessment of the effects of climate change on European agriculture. We employ an empirical analysis on data from 1992–2009 in European regions. Annual yields are modelled as a function of weather variables, production prices and control variables.

We find significant effects of climate variation both on the mean and the variance of wheat and corn yields. Our findings show that variation of prices have no significant impacts on wheat yields before the 1999 CAP reform in the northern regions of Europe, *i.e.*, regions in which production is relatively more important. For corn, prices are also



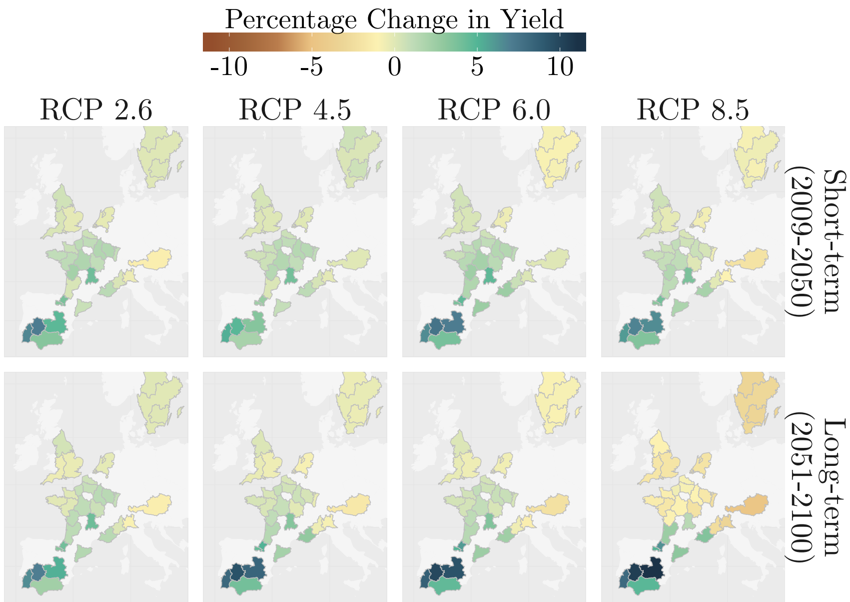
Note: The graphs show the evolution up to 2100 of predicted annual wheat yields for each scenario (RCPs 2.6, 4.5, 6.0, and 8.5). The values are aggregated for northern regions (top) and for southern regions (bottom). Loess estimates of the predicted yields are represented by the dashed lines and accompanied by a 95% confidence interval. The dotted horizontal lines represent the average value of historical predicted wheat yields (1991–2009).

FIGURE 3.3: Predicted Wheat Yields (100kg per ha) Under Different Climate Scenarios



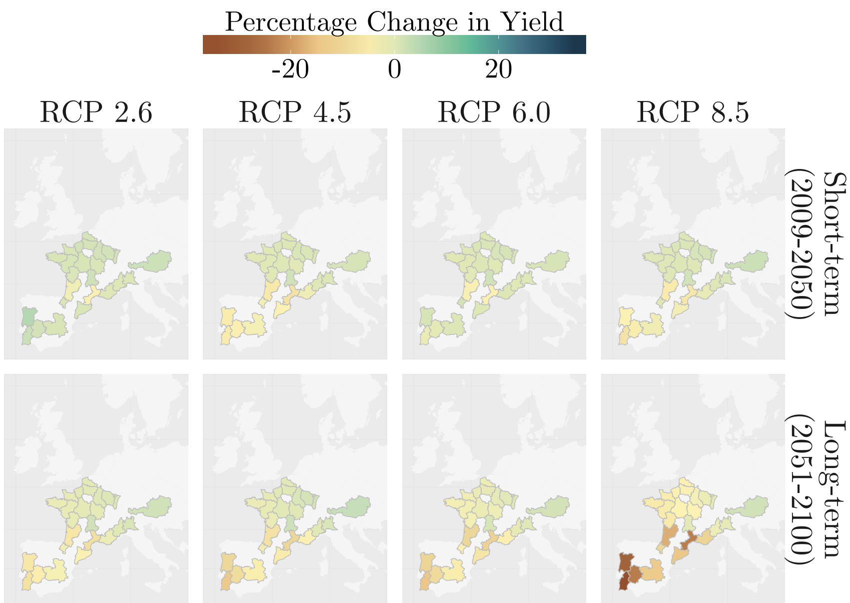
Note: The graphs show the evolution up to 2100 of predicted annual corn yields for each scenario (RCPs 2.6, 4.5, 6.0, and 8.5). The values are aggregates for northern regions (top) and for southern regions (bottom). Loess estimated of the predicted yields are represented by the dashed lines and accompanied by a 95% confidence interval. The dotted horizontal lines represent the average value of historical predicted corn yields (1991–2009).

FIGURE 3.4: Predicted Corn Yields (100kg per ha) Under Different Climate Scenarios



Notes: Values in each region represent the percent change in average predicted wheat yields over the short run period (2009–2050, upper panels) or the long run period (2051–2100, lower panels) compared to average predicted wheat yields over the baseline period (1991–2009).

FIGURE 3.5: Regional Changes in Wheat Yields Under Different Climate Scenarios



Notes: Values in each region represent the percent change in average predicted corn yields over the short run period (2009–2050, upper panels) or the long run period (2051–2100, lower panels) compared to average predicted corn yields over the baseline period (1991–2009).

FIGURE 3.6: Regional Changes in Corn Yields Under Different Climate Scenarios

TABLE 3.5: Effect of Climate Change on Wheat and Corn Yield (percentage change)

Climate scenarios	Temporal Range	Model	Wheat Yield	Corn Yield
RCP 2.6	Short-term (2009-2050)	North	0.82 (1.10)	1.04 (0.55)
		South	3.46 (2.42)	0.58 (2.47)
	Long-term (2051-2100)	North	0.47 (1.09)	−0.12 (0.87)
		South	3.61 (2.21)	−4.40 (2.33)
RCP 4.5	Short-term (2009-2050)	North	0.84 (0.89)	0.28 (0.50)
		South	2.53 (1.71)	−3.94 (1.80)
	Long-term (2051-2100)	North	0.14 (0.96)	0.17 (1.15)
		South	5.08 (2.87)	−7.15 (3.84)
RCP 6.0	Short-term (2009-2050)	North	0.95 (1.19)	0.40 (0.56)
		South	4.45 (2.12)	−0.57 (1.71)
	Long-term (2051-2100)	North	0.20 (1.12)	−0.91 (1.05)
		South	5.50 (3.15)	−8.25 (3.93)
RCP 8.5	Short-term (2009-2050)	North	0.31 (1.13)	0.62 (0.63)
		South	3.88 (2.08)	−3.34 (2.36)
	Long-term (2051-2100)	North	−1.74 (1.21)	−2.65 (1.95)
		South	6.05 (3.10)	−19.88 (8.74)

Notes: Short-term and long-term refer to climate conditions over 2009–2050 and 2051–2100, respectively. Numbers in parentheses are standard deviations.

positively linked to yields in northern regions, but the PAC reform has not significantly changed this relationship.

Four different climate scenarios were proposed to observe changes in wheat and corn annual yields. These scenarios reflect the projections of greenhouse gas concentration until the end of the 21st century. They exhibit both spatial and temporal heterogeneity. Overall, annual wheat yields rise under each scenario, compared to yields predicted by our estimations based on historical climate values. Over time, these gains get higher in the south but approach zero in the north. Projected corn yields under the four climate scenarios tested are less optimistic. Even if some small gains in corn yields would be experienced in the short-run in northern regions, they would become losses in the long-run. Losses would be even higher for regions in southern Europe.

Chapter 4

Climate Change and Business Cycles

Joint work with Gauthier Vermandel (Paris Dauphine University)

1 Introduction

The prospect of considerable climate change and its potentially large impacts on economic well-being are central concerns for the scientific community and policymakers. Along with a forecast increase in global mean temperature of 1 to 4 degrees Celsius above 1990 levels, the Intergovernmental Panel on Climate Change (IPCC) forecasts a rise in both variability and frequency of extreme events, such as droughts (Edenhofer et al., 2014). The intensification of extreme drought events is currently emerging as one of the most important facets of global warming, which may have large macroeconomic implications, particularly for the agricultural sector.

Many efforts have been made to assess the potential economic impact of climate change (Nordhaus, 1994; Tol, 1995; Fankhauser and Tol, 2005), especially its consequences on agricultural systems (Adams et al., 1998; Fischer et al., 2005; Deschênes and Greenstone, 2007). As climatic factors enter into the production function as direct inputs, any important variation in weather conditions has a large effect on agricultural production. From a policymaker perspective, the evaluation of the economic costs incurred from climate shocks has become a crucial element in the decision-making process to implement measures that would offset potential harmful effects on the economy and in turn on social welfare. These very specific macroeconomic costs, generated by variable weather conditions, are particularly challenging for agriculture-based economies, as well as for developing countries, and may undermine world food security (Edenhofer et al., 2014).

Given the remaining uncertainties around the economic costs of variable weather conditions, the main objective of this chapter is to provide a quantitative evaluation of the effects of weather shocks on the business cycles of an economy. We develop an original dynamic stochastic general equilibrium model (DSGE) that incorporates a weather-sensitive agricultural sector into the canonical New Keynesian model. Then, we apply state-of-art Bayesian techniques to determine the implications of weather shocks on business cycles. In the recent literature, only a few papers examine the link between macroeconomic variables and environmental economics using DSGE models in an RBC framework (Fischer and Springborn, 2011; Heutel, 2012; Dissou and Karnizova, 2016) or a New Keynesian setup (Annicchiarico and Di Dio, 2015). While these studies focus on optimal environmental policies, this study investigates the implications of weather shocks on short-run macroeconomic fluctuations. Once estimated, the model is amenable to the analysis of climate change. As climate is assumed to be a stationary process in our study, an analysis of changes in the mean of the climate variable is irrelevant. However, changes in the variance of the climate variable and the underlying impacts on the business cycles can be examined.

This analysis uses data from a small open economy, New Zealand. The reasons for this choice of country are threefold. First, the agricultural sector represents a substantial part of the country's output (around 7% according to the World Bank), making New Zealand highly dependent on weather conditions. In particular, Buckle et al. (2007) underline the importance of weather variations as a source of aggregate fluctuations, along with international trade price shocks, using a structural VAR model for New Zealand. Second, New Zealand is small enough to be subject to relatively homogeneous climatic conditions over its land area.[1] Third, the exercise requires an important number of time series, some of which are not available for developing economies.

To describe New Zealand's economic situation, we develop a standard small open economy model, as in Galí and Monacelli (2005), which is characterized by utility maximizing households that consume domestically and imported goods with some degree

[1] We attempted a similar exercise for a developing economy, namely, India, but the result was not as clear, as India's land area is too vast, resulting in strongly smoothed extreme climate events. Providing a robust analysis for large economies requires a regional approach that is too challenging for a DSGE model.

of nominal rigidity on good prices. We depart from this framework by splitting production into two contrasting sectors: the agricultural sector and the non-agricultural sector. While the latter is standard, the originality of this study lies in the introduction of an agricultural sector facing exogenous weather inputs affecting both agricultural production function and demand for intermediate goods.

Once estimated consistently with the empirical exercise of Buckle et al. (2007), our DSGE model reveals that weather shocks play an important role in explaining macroeconomic fluctuations over the sample period. Drought events are followed by a drop in agricultural output, as in Kamber et al. (2013), and they are responsible for persistent variations in agricultural prices and total output. Our framework, however, highlights the absence of anticipation of weather shocks by farmers one quarter (or more) ahead. Furthermore, the decomposition of the forecast error variance shows that weather shocks remarkably drive the variance in agricultural production and prices. For aggregate output and total demand, the main drivers are, unsurprisingly, supply and demand side factors, respectively; weather shocks only play a modest role in explaining the fluctuations. However, this role grows over time. Moreover, the historical decomposition of business cycles shows that large drought events that occurred in New Zealand in 2008, 2010, and 2013 contributed negatively to output fluctuations and were accompanied by an important inflation increase that clears imbalances in the market for agricultural goods. Finally, in an attempt to investigate the potential impact of climate change on aggregate fluctuations, we alter the variance of the weather shock according to four different climate scenarios. Our results show an increase in the variability of key macroeconomic variables, such as output prices, production or inflation, in all but the optimistic scenario. Specifically, in the best-case scenario, where the standard deviation of the weather shock diminishes by 5.29%, the standard deviations of agricultural output and prices decrease by 2.18% and 1.63%, respectively. In the worst-case scenario, which is characterized by a 20.46% increase in the standard deviation of the weather shock, the standard deviation of agricultural output and prices rises by 11.47% and 9%, respectively.

The remainder of this chapter is organized as follows: section 2 sketches the dynamic stochastic general equilibrium model. Section 3 presents the estimation of the DSGE model. Section 4 discusses the propagation of a weather shock, assesses the consequences of a drought and its implication in terms of business cycles statistics, presents the historical variance decomposition of the main aggregates (gross domestic product, agricultural production, agricultural production price inflation), and provides a quantitative assessment of the implications of weather shocks under different climate projection scenarios for aggregate fluctuations. Section 5 concludes.

2 The Model

This section is devoted to a formal presentation of the DSGE model. Our model is two-sector, two-good economy in a small open economy setup with standard New Keynesian nominal frictions and a flexible exchange rate regime.[2] The home economy, *i.e.,* New Zealand, is populated by households, intermediate goods and final goods agricultural and non-agricultural firms, and a central bank. Intermediate producers in each sector enjoy market power to maximise their profits and produce differentiated goods. Final goods producers use a packing technology to aggregate both home and foreign intermediate goods to produce a homogeneous good sold to households. The final product is a composite of domestically produced and imported goods, thus creating a trading channel adjusted by the real exchange rate. Nominal rigidities in the agricultural and non-agricultural sectors generate inflation dynamics that are damped by the central bank though the adoption of an inflation targeting regime. This section presents the main components of the model.[3]

2.1 Households

There is a continuum $j \in [0,1]$ of identical households that consume, save and work in intermediate goods firms. The representative household maximises the welfare index expressed as the expected sum of utilities discounted by $\beta \in (0,1)$:

$$\mathbb{E}_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\sigma_C} \left(C_{jt+\tau} - hC_{t-1+\tau} \right)^{1-\sigma_C} \exp\left(\frac{\sigma_C - 1}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right) \right], \tag{4.1}$$

[2] Our small open economy setup includes two countries. The home country (here, New Zealand) participates in international trade but is too small compared to its trading partners to cause aggregate fluctuations in world output, price and interest rate. The foreign country, representing most of the trading partners of the home country, is thus not affected by macroeconomic shocks from the home country, but its own macroeconomic developments affect the home country through the trade balance and the exchange rate.

[3] A list of symbols used in this chapter is provided in appendix C, in tables C.1 to C.4, for the household bloc, the intermediate goods firms block, the final goods firms block, and the remaining equations, respectively.

where variable C_{jt} is the consumption index, $h \in [0,1]$ is a parameter that accounts for external consumption habits, h_{jt} is a labour effort index for the agricultural and non-agricultural sectors, and σ_C and σ_H represent consumption aversion and labour disutility, respectively. Following the seminal contribution of Smets and Wouters (2007), households preferences are assumed to be non-separable in consumption, so an increase in hours worked has a positive effect on the marginal utility of consumption.[4]

The representative household allocates total consumption C_{jt} between two types of consumption goods produced by the non-agricultural and agricultural sectors denoted C_{jt}^N and C_{jt}^A respectively. The CES consumption bundle is determined by:

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}}(C_{jt}^N)^{\frac{\mu-1}{\mu}} + \varphi^{\frac{1}{\mu}}(C_{jt}^A)^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}}, \tag{4.2}$$

where $\mu \geq 0$ denotes the substitution elasticity between the two types of consumption goods, and $\varphi \in [0,1]$ is the fraction of agricultural goods in the household's total consumption basket. The corresponding consumption price index thus reads as follows: $P_t^C = [(1-\varphi)\left(P_{y,t}^N\right)^{1-\mu} + \varphi(P_{y,t}^A)^{1-\mu}]^{\frac{1}{1-\mu}}$, where $P_{y,t}^N$ and $P_{y,t}^A$ are the final prices of non-agricultural and agricultural goods, respectively.[5]

Following Iacoviello and Neri (2010), we introduce imperfect substitutability of labour supply between the agricultural and non-agricultural sectors to explain co-movements at the sector level by defining a CES labour disutility index:

$$h_{jt} = \left[n\left(h_{jt}^N\right)^{1+\iota} + (1-n)\left(h_{jt}^A\right)^{1+\iota}\right]^{1/(1+\iota)}. \tag{4.3}$$

The labour disutility index consists of hours worked in the non-agricultural sector h_{jt}^N and agriculture sector h_{jt}^A, with n denoting the relative share of employment in the non-agricultural sector. Reallocating labour across sectors is costly and is governed by the substitutability parameter $\iota \geq 0$.[6]

[4]We refer the reader to Greenwood et al. (1988) for a discussion of the implications of non-separable preferences on business cycles.

[5]Demand for each type of final good is a fraction of the total consumption index adjusted by its relative price: $C_{jt}^N = (1-\varphi)\left(P_{y,t}^N/P_t^C\right)^{-\mu} C_{jt}$ and $C_{jt}^A = \varphi\left(P_{y,t}^A/P_t^C\right)^{-\mu} C_{jt}$.

[6]If ι equals zero, hours worked across the two sectors are perfect substitutes, leading to a negative correlation between the sectors that is not consistent with the data. Positive values of ι capture some degree of sector specificity and imply that relative hours respond less to sectoral wage differentials.

Expressed in real terms and dividing by the consumption price index P_t^C, the budget constraint for the representative household can be represented as:

$$\sum_{s=N,A} \chi_S w_t^s h_{jt}^s + \frac{\Pi_{jt}}{P_t^C} + \frac{R_{t-1}}{\pi_t^C} b_{jt-1} + e_t \frac{R_{t-1}^*}{\pi_t^C} b_{jt-1}^* = C_{jt} + b_{jt} + e_t b_{jt}^* + \frac{P_{y,t}^N}{P_t^C} e_t \Phi_B(b_{jt}^*). \tag{4.4}$$

The income of the representative household is made up of labour income with a real wage w_t^s in each sector,[7] profits Π_{jt} generated by imperfect competition in goods, and real riskless domestics bonds b_{jt} and foreign bonds b_{jt}^*. Domestic and foreign bonds are remunerated at a domestic R_{t-1} and a foreign R_{t-1}^*, respectively, nominal gross interest rates decided by central banks of each country and adjusted by the domestic inflation rate $\pi_t^C = P_t^C / P_{t-1}^C$. Household's foreign bonds purchases are affected by the nominal exchange rate e_t (an increase in e_t can be interpreted as an appreciation of the domestic exchange rate). The household's expenditure side includes its consumption basket C_{jt}, bonds and risk-premium cost $\Phi(b_{jt}^*)$=$0.5\chi_B (b_{jt}^*)^2$ paid in terms of domestic final goods at a market price $P_{y,t}^N$.[8] Parameter $\chi_B > 0$ denotes the magnitude of the cost paid by domestic households when purchasing foreign bonds.

The first-order conditions solving the household's optimization problem are obtained by maximizing welfare index in eq. (4.1) under the budget constraint in eq. (4.4) given the labour sectoral re-allocation cost in eq. (4.3). First, the marginal utility of consumption is determined by:[9]

$$\lambda_t^c = \exp(\frac{\sigma_C - 1}{1+\sigma_H} h_{jt}^{1+\sigma_H}) \left(C_{jt} - hC_{t-1}\right)^{-\sigma_C}. \tag{4.5}$$

The first-order condition determines the household labour supply in each sector:

$$w_t^N = h_{jt}^{\sigma_H} \frac{n}{\chi_N} \left(\frac{h_{jt}^N}{h_{jt}}\right)^{\iota} \left(C_{jt} - hC_{t-1}\right), \tag{4.6}$$

$$w_t^A = h_{jt}^{\sigma_H} \frac{(1-n)}{\chi_A} \left(\frac{h_{jt}^A}{h_{jt}}\right)^{\iota} \left(C_{jt} - hC_{t-1}\right). \tag{4.7}$$

[7]Real labour income is affected by $\chi_s > 0$, a sector-specific shift parameter that allows us to calibrate the steady state of hours worked in each sector. This is a common assumption in real business cycle models.

[8]This cost function aims at removing a unit root component that emerges in open economy models without affecting the steady state of the model. See Schmitt-Grohé and Uribe (2003) for a discussion of closing open economy models.

[9]In equilibrium, the marginal utility of consumption equals the Lagrange multiplier λ_t^c associated with the household budget constraint.

where w_t^N and w_t^A are the real wages in the non-agricultural sector and the agricultural sector, respectively.

The Euler condition on domestic bonds that determines the optimal consumption path is:

$$\beta \mathbb{E}_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} \frac{1}{\mathbb{E}_t \left\{ \pi_{t+1}^C \right\}} \right\} = \frac{1}{R_t}. \tag{4.8}$$

Finally, the Euler condition on foreign bonds, after substituting the Lagrange multiplier, can be expressed as the real exchange rate determination under incomplete markets:

$$\mathbb{E}_t \left\{ \frac{e_{t+1}}{e_t} \right\} = \frac{R_t}{R_t^*}(1 + \chi_B p_{y,t}^N b_{jt}^*), \tag{4.9}$$

where $p_{y,t}^N = P_{y,t}^N / P_t^C$ denotes the relative price of final goods with respect to the consumption price index.

We define the real exchange rate as the ratio of final goods prices expressed in a common currency:

$$rer_t = e_t \frac{P_t^{C*}}{P_t^C}, \tag{4.10}$$

where P_t^{C*} denotes the foreign price.

2.2 Final Goods Firms

The firm block is populated by two groups of agents: intermediate goods firms and final goods firms. Intermediate goods firms produce differentiated goods $i \in [0, 1]$, decide on labour on a perfectly competitive inputs market, and set prices according to a Rotemberg (1982) technology. Final goods producers act as goods bundlers by combining national and foreign intermediate goods to produce a homogeneous non-tradable final good that will be sold to domestic households.

In each sector $s = \{N, A\}$, where N and A denote the non-agricultural and agricultural sectors, respectively, we assume that the production of the final good is performed as in Rabanal and Tuesta (2010). A continuum of final goods firms purchases a composite of intermediate home goods X_t^s, and a composite of intermediate foreign-produced goods X_t^{s*} to produce a differentiated final good product Y_t^s using the following CES technology:

$$Y_t^s = \left[(1 - \alpha_s)^{\frac{1}{\mu_s}} \left(X_t^s \right)^{\frac{(\mu_s - 1)}{\mu_s}} + \alpha_s^{\frac{1}{\mu_s}} \left(X_t^{s*} \right)^{\frac{(\mu_s - 1)}{\mu_s}} \right]^{\frac{\mu_s}{(\mu_s - 1)}}, \tag{4.11}$$

where α_s denotes the share of foreign-produced goods that are used for the production of the final good, and μ_s is the elasticity of substitution between domestically produced and imported intermediate goods in both countries. A value of $\alpha_s = 0$ implies the autarky of this market, while $\alpha_s < 0.5$ reflects a home bias in the preferences of firms. The corresponding sectoral production price index is given by: $P^s_{y,t} = [(1-\alpha_s)(P^s_t)^{1-\mu_s} + \alpha_s(e_t P^{s*}_t)^{1-\mu_s}]^{1/(1-\mu_s)}$, for $s = \{N, A\}$.

The composite intermediate goods for the non-agricultural sector bought at home and abroad are $X^N_t = (\int_0^n (X^N_{it})^{(\epsilon_N-1)/\epsilon_N} \mathrm{d}i)^{\epsilon_N/(\epsilon_N-1)}$ and $X^{N*}_t = (\int_0^n (X^{N*}_{it})^{(\epsilon_N-1)/\epsilon_N} \mathrm{d}i)^{\epsilon_N/(\epsilon_N-1)}$, while for the agricultural sector, we have $X^A_t = (\int_n^1 (X^A_{it})^{(\epsilon_A-1)/\epsilon_A} \mathrm{d}i)^{\epsilon_A/(\epsilon_A-1)}$ and $X^{A*}_t = (\int_n^1 (X^{A*}_{it})^{(\epsilon_A-1)/\epsilon_A} \mathrm{d}i)^{\epsilon_A/(\epsilon_A-1)}$. For each sector $s = \{A, N\}$, a parameter $\epsilon_s > 1$ is the elasticity of substitution between the types of intermediate goods. Since goods are imperfect substitutes, firms are able to deviate from the perfectly competitive equilibrium by imposing a margin on their selling prices. The packing activity delivers the following price index for each sector: $P^N_t = [1/n \int_0^n P^{N\,1-\epsilon_N}_{it} \,\mathrm{d}i]^{1/(1-\epsilon_N)}$ and $P^A_t = [1/(1-n)\int_n^1 P^{A\,1-\epsilon_A}_{it} \,\mathrm{d}i]^{1/(1-\epsilon_A)}$, ensuring that profits are always zero.

At the optimum, the demand functions for home and foreign goods produced in sector s are given by:

$$X^s_{it} = (1-\alpha_s)\left(\frac{P^s_t}{P^s_{y,t}}\right)^{-\mu_s}\left(\frac{P^s_{it}}{P^s_t}\right)^{-\epsilon_s} Y^s_t \text{ and } X^{s*}_{it} = \alpha_s\left(e_t\frac{P^{s*}_t}{P^s_{y,t}}\right)^{-\mu_s}\left(\frac{P^{s*}_{it}}{P^{s*}_t}\right)^{-\epsilon_s} Y^s_t. \tag{4.12}$$

2.3 Intermediate Goods Firms

In each sector, intermediate goods firms produce an intermediate goods that is used by final goods firms to produce the homegeneous non-tradable final good.

2.3.1 Agricultural Production and Weather Variability

To investigate the implications of weather variations as a source of aggregate fluctuation, we introduce into the model a weather variable, denoted ε^W_t, that captures variations in soil moisture affecting the production process of farmers. The measure we use is based on soil moisture deficit observations calculated from the daily water balance.[10] A positive realization of ε^W_t depicts a prolonged episode of dryness that

[10] The soil moisture variable measures the net impact of rainfall entering the pasture root zone in the soil, which is then lost from this zone as a result of evapotranspiration or use of water by plants.

damages agricultural output and generates inflation pressures. We assume that the aggregate drought index follows a stochastic exogenous process driven by two shocks:

$$\varepsilon_t^W = (1-\rho_W) + \rho_W \varepsilon_{t-1}^W + \eta_t^W + \tilde{\eta}_{t-1}^W, \qquad \rho_W \in [0,1), \tag{4.13}$$

The first shock, denoted η_t^W, is a traditional shock to the real business cycle that impacts the level of soil moisture in the same period in which farmers see it. The second, $\tilde{\eta}_{t-1}^W$, is a news shock and is differentiated from the former in that farmers observe a weather news shock in advance (here, one quarter).[11] Thus, this shock allows us to evaluate whether farmers are anticipating drought events one quarter in advance by capturing macroeconomic fluctuations one quarter before the realization of the weather shock.[12]

To bridge weather variations with business cycle fluctuations, we define a damage variable d_t determining how variable weather conditions $\log(\varepsilon_t^W)$ may induce inertial aggregate fluctuations:

$$d_t = \rho_d d_{t-1} + \log(\varepsilon_t^W), \qquad \rho_d \in [0,1), \tag{4.14}$$

where ρ_d captures some persistence of damage after an adverse drought event shock. Here, it is important to disentangle the parameter ρ_W from eq. (4.13) and ρ_d from eq. (4.14): the autoregressive component ρ_W captures the estimated persistence of a drought shock, while ρ_d catches the persistence of its damages. The main underlying motivation is that damages to the economy might be more persistent than the weather shock itself, as showed by the VAR models.[13]

The production component of agriculture is strongly inspired by Restuccia et al. (2008) to the extent that agricultural output is Cobb-Douglas in land, intermediate inputs, and labour inputs.[14] In addition to this modeling choice, we introduce a damage function

[11] We follow the news-driven business cycles literature, as exemplified by Beaudry and Portier (2006), Barsky and Sims (2011) and Schmitt-Grohé and Uribe (2012), to introduce climate-news shocks as a source of macroeconomic fluctuation.

[12] Anticipating the results from the estimation exercise, we have evaluated the ability of farmers to expect weather shocks more than one quarter in advance; however, we find evidence that farmers are not able to predict drought events and that they are rather surprised by weather shocks.

[13] We refer to Buckle et al. (2007) and Kamber et al. (2013) for VAR models highlighting the hysteresis effects of weather shocks on business cycles.

[14] We refer to Mundlak (2001) for discussions of related conceptual issues and empirical applications regarding the functional forms of agricultural production. In an alternative version of our model based on a CES agricultural production function, the fit of the DSGE model is not improved, and the identification of the CES parameter is weak.

$\Gamma_X(\cdot)$ in the spirit of Integrated Assessment Models, which connects the weather to agricultural output.

Each representative firm $i \in [n, 1]$ operating in the agricultural sector has the following production function:

$$X_{it}^A = \varepsilon_t^Z Z_{it}^{\omega} \left(\left(\Gamma_X \left(d_t, d_{t-1} \right) \bar{L}_i \right)^{1-\sigma} \left(\kappa_i H_{it}^A \right)^{\sigma} \right)^{1-\omega}, \tag{4.15}$$

where X_{it}^A is the production function of the intermediate agricultural good that combines a (fixed) land endowment $\bar{L}_i$ for each farmer i, labour demand H_{it}^A and non-agricultural inputs Z_{it}. Production is subject to an economy-wide technology shock ε_t^Z.[15] The parameter $\omega \in [0, 1]$ is the elasticity of output to intermediate inputs, $\sigma \in [0, 1]$ denotes the share of production/land in the production process of agricultural goods, and $\kappa_i > 0$ is a technology parameter endogenously determined in the steady state. The economy-wide technology shock ε_t^Z affects both agricultural and non-agricultural sectors by capturing fluctuations associated with declining hours worked and prices coupled with increasing output.

Agricultural production is tied up with exogenous weather conditions through a damage function $\Gamma_X(\cdot)$ that alters land productivity. This function has a simple form with one lag aiming at capturing the hump-shaped response of output to weather shock:

$$\Gamma_X \left(d_t, d_{t-1} \right) = 1 + \gamma_0^X d_t + \gamma_1^X d_{t-1}, \tag{4.16}$$

where $\gamma_0^X, \gamma_1^X \in (-\infty, +\infty)$ are elasticities that are estimated agnostically (*i.e.*, without tight priors) during the estimation exercise. In our setup, we are interested in the short-run implications of weather shocks, leaving aside the neutral long-run effects with $\Gamma_X \left(\bar{d}, \bar{d} \right) = 1$, where $\bar{d}$ denotes the (zero) deterministic steady state of damages induced by drought events. The parameter γ_1^X captures the lagged response of output after drought events. The introduction of this parameter is motivated by the time prices usually take to adjust to climate shocks, as assumed by Bloor and Matheson (2010).

In addition to this damage function for output, inputs costs are affected by a similar function. The real costs paid by farmers read as follows:

$$w_t^A H_{it}^A + p_t^N Z_{it} \Gamma_Z \left(d_t, d_{t-1} \right), \tag{4.17}$$

[15] Technology is characterized as an $AR(1)$ shock process: $\varepsilon_t^Z = 1 - \rho_Z + \rho_Z \varepsilon_{t-1}^Z + \eta_t^Z$ with $\eta_t^Z \sim \mathcal{N}(0, \sigma_Z)$, where $\rho_A \in [0, 1)$ denotes the $AR(1)$ term in the technological shock process.

where w_t^A is the real wage offered to households hired in the agricultural sector, and $p_t^N = P_t^N / P_t^C$ denotes the relative price of intermediate goods, with P_t^C as the consumer price index. The demand for intermediate goods Z_{it} is affected by $\Gamma_Z\left(d_t, d_{t-1}\right)$, which aims at capturing extra consumption of intermediate goods following a drought event. A drought shock increases the feed budget, as dairy cattle require more water as temperature, humidity and production levels rise. Farming activities also demand more water to offset soil dryness by increasing field irrigation. This damage function captures the demand effects in the intermediate sector, and the shape of this damage function reads as in eq. (4.16) with different elasticities denoted γ_0^Z and $\gamma_1^Z \in (-\infty, +\infty)$.

To introduce nominal rigidities, we assume that firms must solve a two-stage problem. In the first stage, the real input price w_t^N is taken as given, firms rent inputs H_{it}^N and Z_{it} in a perfectly competitive factor market in order to minimize costs subject to the production constraint. Each firm maximises profits:

$$\max_{\left\{Z_{it}, H_{it}^N\right\}} mc_{it}^A X_{it}^A - w_t^A H_{it}^A - \Gamma_Z\left(d_t, d_{t-1}\right) p_t^N Z_{it}$$

under the supply constraint in eq. (4.15). The variable mc_{it}^A denotes the real marginal cost of producing an additional agricultural good.

The cost-minimization problem ensures that the real agricultural wage is directly driven by the marginal product of labour:

$$w_t^A = mc_t^A \left(1 - \omega\right) \sigma \frac{X_t^A}{H_t^A}. \tag{4.18}$$

The second cost-minimizing condition is obtained from the marginal product of intermediate consumption Z_t and provides the optimal demand for intermediate goods from the farmer:

$$Z_t = \omega \frac{mc_t^A}{\Phi_Z\left(d_t, d_{t-1}\right) p_t^N} X_t^A. \tag{4.19}$$

In the second stage, the intermediate goods firm operates monopolistically and sets the retail price according to a Rotemberg (1982) technology. Intermediate goods firms face adjustment costs with price changes AC_{it}^A defined according to: $AC_{it}^A = 0.5\kappa_A(P_{it}^A / P_{it-1}^A - (\pi_{t-1}^A)^{\xi_A})^2$, where κ_A is the cost of adjusting prices, and ξ_A is the coefficient that measures the rate of indexation to the past rate of inflation of intermediate goods, $\pi_{t-1}^A = P_{t-1}^A / P_{t-2}^A$. These costs are paid in terms of the final goods at a market price of $P_{y,t}^N$. Given this price adjustment cost specification and replacing the demand function for final goods firms, the problem of the representative firms becomes dynamic:

$$\mathbb{E}_t \sum_{\tau=0}^{+\infty} \frac{\lambda^c_{t+\tau}}{\lambda^c_t} \beta^{\tau} \left[\frac{P^A_{it+\tau}}{P^C_{t+\tau}} \left(\frac{P^A_{it+\tau}}{P^A_{t+\tau}} \right)^{-\epsilon_A} X^A_{t+\tau} - mc^A_{it+\tau} X^A_{it+\tau} - p^N_{y,t+\tau} Y^A_{t+\tau} AC^A_{it+\tau} \right]. \tag{4.20}$$

The variables mc^A_{it} and $p^A_{y,t}$ are the real marginal cost and the relative price of non-agricultural final goods. Since firms are owned by households, they discount expected profits using the same discount factor as households ($\beta^{\tau} \lambda^c_{t+\tau} / \lambda^c_t$).[16] Anticipating symmetry between firms with $P^A_t = P^A_{it}$, the first-order condition is:

$$\begin{aligned} (1-\epsilon_A)\, p^A_t + \epsilon_A mc^A_t - p^N_{y,t} \frac{Y^A_t}{X^A_t} \kappa_A \left(\pi^A_t - (\pi^A_{t-1})^{\xi_A} \right) \pi^A_t \\ + \kappa_A \beta \mathbb{E}_t \left\{ \frac{\lambda^c_{t+1}}{\lambda^c_t} p^N_{y,t+1} \frac{Y^A_{t+1}}{X^A_t} \left(\pi^A_{t+1} - (\pi^A_t)^{\xi_A} \right) \pi^A_{t+1} \right\} = 0. \end{aligned} \tag{4.21}$$

2.3.2 Non-Agricultural Intermediate Production

Each representative intermediate goods firm $i \in [0, n]$ has the following technology:

$$X^N_{it} = \varepsilon^Z_t H^N_{it}, \tag{4.22}$$

where X^N_{it} is the production of the i^{th} intermediate goods firm that combines labour demand H_{it} and technology ε^Z_t.

Intermediate goods producers solve a two-stage problem. In the first stage, the real input price w^N_t is taken as given, and these firms rent inputs H^N_{it} in a perfectly competitive factor markets in order to minimize costs subject to the production constraint:

$$\max_{\{X^N_{it}, H^N_{it}\}} mc^N_{it} X^N_{it} - w^N_t H^N_{it} + \lambda^n_t \left[X^N_{it} - \varepsilon^Z_t H^N_{it} \right].$$

The first-order condition leads to $i)$ $mc^N_{it} = \lambda^n_t$ and $ii)$ the real marginal cost expression:

$$mc^N_{it} = mc^N_t = \frac{w^N_t}{\varepsilon^Z_t}. \tag{4.23}$$

In the second stage, the intermediate goods firm operates monopolistically and sets the retail price according to a Rotemberg (1982) technology. Intermediate goods firms face

[16] The stochastic discount factor is endogenously determined by the Euler condition of households. In equilibrium, the stochastic discount is inversely related to the real interest rate.

adjustment costs on price changes AC_{it}^N defined according to $AC_{it}^N = 0.5\kappa_N(P_{it}^N/P_{it-1}^N - (\pi_{t-1}^N)^{\xi_N})^2$, where κ_N is the cost of adjusting prices, and ξ_N is the coefficient that measures the rate of indexation to the past rate of inflation of intermediate goods $\pi_{t-1}^N = P_{t-1}^N/P_{t-2}^N$. These costs are paid in terms of final goods at a market price $P_{y,t}^N$. Given this price adjustment cost specification, the problem of the representative firms becomes dynamic:

$$\mathbb{E}_t \sum_{\tau=0}^{+\infty} \frac{\lambda_{t+\tau}^c}{\lambda_t^c} \beta^\tau \left[\frac{P_{it+\tau}^N}{P_{t+\tau}^C} \left(\frac{P_{it+\tau}^N}{P_{t+\tau}^N} \right)^{-\epsilon_N} X_{t+\tau}^N - \varepsilon_{t+\tau}^N mc_{it+\tau}^N X_{it+\tau}^N - p_{y,t+\tau}^N Y_{t+\tau}^N AC_{it+\tau}^N \right], \tag{4.24}$$

where ε_t^N is an AR(1) markup shock that aims at capturing the external factors driving the inflation rate, which are not included in the model such as commodity prices.

Anticipating symmetry between firms with $P_t^N = P_{it}^N$, the first- order condition reads:

$$\begin{aligned} (1-\epsilon_N)\, p_t^N + \epsilon_N \varepsilon_t^N mc_t^N - p_{y,t}^N \frac{Y_t^N}{X_t^N} \kappa_N \left(\pi_t^N - (\pi_{t-1}^N)^{\xi_N} \right) \pi_t^N \\ + \kappa_N \beta \mathbb{E}_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} p_{y,t+1}^N \frac{Y_{t+1}^N}{X_t^N} \left(\pi_{t+1}^N - (\pi_t^N)^{\xi_N} \right) \pi_{t+1}^N \right\} = 0. \end{aligned} \tag{4.25}$$

2.4 Monetary Policy

The central bank reacts to fluctuations in price, activity and external imbalance. The general expression of the linear interest rule implemented by the central bank can be expressed as:

$$R_t = \left(\bar{R}\right)^{1-\rho} \left(R_{t-1}\right)^{\rho} \left[\left(\pi_t\right)^{\phi_\pi} \left(RER_t\right)^{\phi_E} \right]^{(1-\rho)} \left(\mathcal{Y}_t^D / \mathcal{Y}_{t-1}^D \right)^{\phi_{\Delta Y}} \varepsilon_t^R, \tag{4.26}$$

where $\bar{R}$ is the steady-state interest rate, $\mathcal{Y}_t^D$ is gross domestic product, ε_t^R is an exogenous $AR(1)$ monetary policy shock,[17] ϕ_π, ϕ_E and $\phi_{\Delta Y}$ denote inflation, real exchange rate and GDP growth gap parameters, respectively, that aim to stabilize the economy when it deviates from its steady state. In a small economy context, we follow the definition of monetary policy rules in open economies of Clarida et al. (1998) and estimate ϕ_E. A positive value of ϕ_E induces a reduction in the variance of the real exchange rate.

[17] The monetary policy shock follows a standard $AR(1)$ stochastic process: $\varepsilon_t^R = (1-\rho_R) + \rho_R \varepsilon_{t-1}^R + \varepsilon_t^R$, with $\eta_t^R \sim \mathcal{N}(0, \sigma_R)$, and $0 \leq \rho_R < 1$ the autoregressive term.

2.5 Foreign Economy

Our foreign economy is characterized by a set of five equations that aims at capturing the standard business cycle patterns of the foreign economy. Four equations are taken from the standard New Keynesian framework, namely, the Phillips curve, the IS curve, the Taylor rule and the CES substitution curve between two types of goods. These equations provide the structural relations between aggregate output Y_t^*, agricultural output Y_t^{A*}, inflation π_t^* and the nominal interest rate R_t^*. Most of the parameters and the steady state are symmetric between domestic and the foreign economy for clarity purposes.

The foreign inflation rate is determined by the firm's price setting equation under Rotemberg price adjustment costs:

$$(1-\epsilon_N)+\epsilon_N\chi^* Y_t^* - \kappa^*\left(\pi_t^*-1\right)\pi_t^* + \kappa^*\beta\mathbb{E}_t\left\{\left(\pi_{t+1}^*-1\right)\pi_{t+1}^*\right\}=0. \tag{4.27}$$

Foreign non-agricultural output is determined by the following Euler equation:

$$\beta\mathbb{E}_t\left\{\frac{Y_t^*}{Y_{t+1}^*}\frac{1}{\pi_{t+1}^*}\right\}=\frac{\varepsilon_t}{R_t^*} \tag{4.28}$$

where ε_t^{Y*} is a demand shock characterized by an iid $AR(1)$.

The third relation is the Taylor rule, which is analogous to eq. (4.26):

$$R_t^* = \left(\bar{R}^*\right)^{1-\rho^*}\left(R_{t-1}^*\right)^{\rho^*}\left(((\pi_t^*)^n\left(p_t^{A*}/p_{t-1}^{A*}\right)^{1-n})^{\phi_\pi^*}(Y_t^*/\bar{Y}^*)^{\phi_y^*}\right)^{(1-\rho^*)}. \tag{4.29}$$

In this expression, ρ^* is the autocorrelation parameter, ϕ_π^* is the elasticity of the nominal interest rate to the inflation rate, and ϕ_y^* is the elasticity of the nominal interest rate to the output gap. Expression p_t^{A*}/p_{t-1}^{A*} denotes the variation of the relative price index of agricultural goods weighted by the size of the agricultural sector 1-n.

The fourth equation determines the demand for agricultural goods by foreign households. This equation is a reduced-form equation of eq. (4.2), modeling households preferences by substituting agricultural and non-agricultural goods *via*:

$$\frac{Y_t^{A*}}{Y_t^*}=\frac{\varphi}{1-\varphi}\left(\frac{p_t^{A*}}{p_{t-1}^{A*}}\right)^{-\mu},$$

where p_t^{A*} is the relative price of agricultural goods, parameter φ is the share of agricultural goods in the consumption basket, and μ is the substitution parameter. This equation shows that the household's consumption allocation is determined by the gap between variations in the relative price index between agricultural and non-agricultural goods.

Finally, the foreign agricultural price is too volatile to be determined by a New Keynesian Phillips curve. We assume the relative price of foreign agricultural goods is determined by an AR(1) shock process:

$$\varepsilon_t^{A*} = 1 - \rho_A^* + \rho_A^* \varepsilon_{t-1}^{A*} + \eta_t^{A*} \text{ with } \eta_t^{A*} \sim \mathcal{N}(0, \sigma_A^{*2}), \tag{4.30}$$

with relative agricultural prices directly driven by the shock $p_t^{A*} = \varepsilon_t^{A*}$.

In addition, the second exogenous shock affecting the IS curve reads:

$$\varepsilon_t^{Y*} = 1 - \rho_Y^* + \rho_Y^* \varepsilon_{t-1}^{Y*} + \eta_t^{Y*} \text{ with } \eta_t^{Y*} \sim \mathcal{N}(0, \sigma_Y^{*2}). \tag{4.31}$$

2.6 Shocks, Aggregation and Equilibrium Conditions

After (i) aggregating all agents and varieties in the economy, (ii) imposing market clearing on all markets, and (iii) substituting the relevant demand functions, we can deduct the general equilibrium conditions of the model.

First, total demand for non-agricultural goods is as follows:

$$Y_t^N = (1-\varphi)\left(\frac{P_{y,t}^N}{P_t^C}\right)^{-\mu} C_t + \Phi_B(b_{jt}^*) + AC_t^N Y_t^N + AC_t^A Y_t^A, \tag{4.32}$$

while the equilibrium in the intermediate goods market after aggregation is determined by:

$$nX_t^N = (1-\alpha_N)\left(\frac{P_t^N}{P_{y,t}^N}\right)^{-\mu_N} Y_t^N + \alpha_N \left(\frac{1}{e_t}\frac{P_t^N}{P_{y,t}^{N*}}\right)^{-\mu_N} Y_t^{N*} + (1-n)\, Z_t, \tag{4.33}$$

where $nX_t^N = \int_0^n X_{it}^N \,\mathrm{d}i$ is the aggregate supply, and $(1-n)\, Z_t = \int_n^1 Z_{it} \,\mathrm{d}i$ denotes the aggregate demand for domestic intermediate goods from farmers. In this equation, the left side denotes the aggregate production of intermediate goods, while the right side denotes respectively demands from home and foreign (i.e. imports) final goods firms, and also demand for intermediate goods from farmers.

Similarly, for the agricultural sector, the aggregate demand is:

$$Y_t^A = \varphi \left(\frac{P_{y,t}^A}{P_t^C} \right)^{-\mu} C_t, \tag{4.34}$$

and equilibrium in the intermediate market is achieved by the following clearing market condition:

$$(1-n)\, X_t^A = (1-\alpha_A) \left(\frac{P_t^A}{P_{y,t}^A} \right)^{-\mu_A} Y_t^A + \alpha_A \left(\frac{1}{e_t} \frac{P_t^A}{P_{y,t}^{A*}} \right)^{-\mu_A} Y_t^{A*}. \tag{4.35}$$

Turning to the labour market, the market clearing condition between household labour supply and demand from firms in each sector is:

$$\int_0^1 h_{jt}^N \mathrm{d}j = \int_0^n H_{it}^N \mathrm{d}i \text{ and } \int_0^1 h_{jt}^A \mathrm{d}j = \int_n^1 H_{it}^A \mathrm{d}i. \tag{4.36}$$

The law of motion for the total amount of real foreign debt is:

$$b_{jt}^* = \frac{R_{t-1}^*}{\pi_t^C} \Delta e_t b_{jt-1}^* + n \left(p_t^N X_t^N - p_{y,t}^N Y_t^N \right) + (1-n) \left(p_t^A X_t^A - p_{y,t}^A Y_t^A - p_t^N Z_t \right). \tag{4.37}$$

Real domestic absorption ($\mathcal{Y}_t^D$) and aggregate production ($\mathcal{Y}_t^S$) are given by:

$$\mathcal{Y}_t^D = n p_{y,t}^N Y_t^N + (1-n)\, p_{y,t}^A Y_t^A, \tag{4.38}$$

$$\mathcal{Y}_t^S = n p_t^N X_t^N + (1-n) \left(p_t^A X_t^A - p_t^N Z_t \right). \tag{4.39}$$

Finally, the general equilibrium condition is defined as a sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and prices $\{\mathcal{P}_t\}_{t=0}^{\infty}$ such that for a given sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and the realization of shocks $\{\mathcal{S}_t\}_{t=0}^{\infty}$, the sequence $\{\mathcal{P}_t\}_{t=0}^{\infty}$ guarantees simultaneous equilibrium on all markets previously defined.

3 Estimation

The model is estimated using 7 time series with Bayesian methods and quarterly data for New Zealand over the sample period 1989:Q1 to 2014:Q2.[18] We estimate the structural parameters and the sequence of shocks following the seminal contributions of

[18] See appendix 4.1 for more details on the series used in the estimation.

Smets and Wouters (2007) and Christiano et al. (2005). For a detailed description, we refer the reader to the original papers.

3.1 Calibration and Prior Distributions

We fix a small number of parameters that are commonly used in the literature of real business cycle models, including β=0.99, the discount factor; $\bar{h}^N$=$\bar{h}^A$=1, the steady state hours worked per firm normalized to one; and σ_H=2, the labour effort disutility. Regarding the sectoral labour reallocation costs, we fix ι=2.5 (higher than σ_H) in order to obtain a positive correlation between the sectors, as reported by Iacoviello and Neri (2010). Following Smets and Wouters (2007), the substitution parameters for agricultural goods and non-agricultural goods are ϵ_N=ϵ_N=10, implying a quarterly markup of 11%. Regarding the international business cycle parameters, we employ a calibration in line with the small open economy literature. The portfolio adjustment cost on foreign debt is set close to that in Schmitt-Grohé and Uribe (2003), with $\chi_B = 0.01$.[19] The current account is balanced in steady state assuming $\bar{b}^* = \overline{ca} = 0$, and substitution between home and foreign varieties is set at μ_N=μ_A=1.5 for both sectors. Regarding the openness of the goods market, our calibration is strongly inspired by Liu (2006), with a share α_N of exported non-agricultural goods set to 25% and to 30% for agricultural goods α_A to account for the greater internationalization of the agricultural sector. Turning to agricultural sector parameterization, the share of agricultural goods is set to $\varphi = 14\%$, as observed in the consumption basket of New Zealander households, while the relative share of firms operating in the non-agricultural sector is fixed to $n = 0.93$ to obtain an agricultural output-to-GDP ratio that is consistent with the data. In addition, our calibration of the production function relies on Restuccia et al. (2008) with a land-to-employment ratio $\bar{L}_i$=1.4, an income share of labour in agriculture σ=0.70, and an intermediate input-to-output ratio ω=0.40. Finally, for the foreign economy, we select parameters that replicate US business cycles, as it is a leading trading partner of New Zealand: ρ^*=0.8, $\kappa^* = 40$, ϕ_π^*=1.5 and ϕ_y^*=0.125.

The rest of the parameters are estimated using Bayesian methods. Table 4.1 and fig. 4.1 report the prior (and posterior) distributions of the parameters for New Zealand.[20]

[19] The value of this parameter marginally affects the dynamic of the model, but it allows us to remove a unit root component induced by the open economy setup.

[20] The posterior distribution combines the likelihood function with prior information. To calculate the posterior distribution to evaluate the marginal likelihood of the model, the Metropolis-Hastings algorithm is employed. We compute the posterior moments of the parameters using a total generated sample of 400, 000, discarding the first 40, 000, and based on four parallel chains. The scale factor was set in order to deliver acceptance rates of between 20% and 25%. Convergence was assessed by means of

Overall, our prior distributions are either relatively uninformative or consistent with earlier contributions to Bayesian estimations. For a majority of New Keynesian model parameters, *i.e.*, σ_C, h, ξ_N, ξ_A, ρ, ϕ_π, and $\phi_{\Delta y}$, and shock processes parameters, we use the prior distributions imposed by Smets and Wouters (2007). However, some priors have been marginally adjusted to match New Zealand's situation (with more uninformative priors). We discuss the prior information that is not taken from Smets and Wouters (2007). First, since we do not have empirical evidence regarding the substitution parameter on goods μ, we give diffuse prior information on a positive support characterized by a gamma distribution centered on 10, with a deviation of 2. Second, sectoral price adjustment costs κ_N, and κ_A are assumed to be gamma distributed with mean 50 and standard deviation 7.50, which corresponds to an average contract duration of approximately 4.5 quarters in the Calvo model. Third, we evaluate the perspective of real exchange rate targeting by imposing the corresponding policy weight ϕ_E on a prior similar to the output growth weight. Finally, regarding the damage parameter induced by weather shocks, we adopt an agnostic approach using very uninformative prior information. Damage parameters γ_0^X, γ_1^X, γ_0^Z and $\gamma_{1,}^P$, are given a diffuse normal distribution, with the mean and standard deviation set to 0 and 50, respectively. The autoregressiveness coefficient ρ_d of the damage variable is also diffuse, with a beta distribution with mean 0.50 and standard deviation 0.2.

3.2 Posterior Distribution

In addition to the prior distributions, table 4.1 reports the estimation results that summarize the means and the 5th and 95th percentiles of the posterior distributions, while the latter are illustrated in fig. 4.1. According to fig. 4.1, the data were fairly informative, as their posterior distributions did not stay very close to their priors. While our estimates of the standard parameters are in line with the business cycle literature (see, for instance, Smets and Wouters (2007) for the US economy or Liu (2006) for New Zealand), several observations are worth making regarding the means of the posterior distributions of structural parameters.

Contrasting our results with the estimates of Smets and Wouters (2007) for the US economy, consumption appears to be less persistent in New Zealand and more elastic to variations in the real interest rate. Nominal rigidities appear to be stronger in New Zealand. This outcome is consistent with a small open economy characterized by

the multivariate convergence statistics taken from Brooks and Gelman (1998). We estimate the model using the dynare package Adjemian et al. (2011).

TABLE 4.1: Prior and Posterior Distributions of Structural Parameters and Shock Processes

		Prior distributions			Posterior distribution	
		Shape	Mean	Std.	Mean	[5%:95%]
SHOCK PROCESS $AR(1)$						
Productivity	σ_N	IG	0.1	∞	1.99	[1.75:2.16]
Preference	σ_D	IG	0.1	∞	8.39	[7.66:8.93]
Markup non-agricultural	σ_N	IG	0.1	∞	4.69	[4.19:5.07]
Foreign demand	σ_Y^*	IG	0.1	∞	0.62	[0.54:0.69]
Foreign agricultural prices	σ_A^*	IG	0.1	∞	3.89	[3.56:4.14]
Monetary policy	σ_R	IG	0.1	∞	0.30	[0.26:0.33]
Weather (surprise)	σ_W	IG	0.1	∞	0.42	[0.45:0.61]
Weather (news-1q)	$\hat{\sigma}_W$	IG	0.1	∞	0.21	[0.02:0.24]
Productivity (AR term)	ρ_Z	B	0.5	0.2	0.76	[0.74:0.80]
Preference (AR term)	ρ_D	B	0.5	0.2	0.82	[0.79:0.87]
Markup non-agricultural (AR term)	ρ_N	B	0.5	0.2	0.97	[0.96:0.99]
Foreign demand (AR term)	ρ_Y^*	B	0.5	0.2	0.99	[0.99:1.00]
Foreign agricultural prices (AR term)	ρ_A^*	B	0.5	0.2	0.96	[0.95:0.98]
Monetary policy (AR term)	ρ_R	B	0.5	0.2	0.19	[0.14:0.25]
Weather (AR term)	ρ_W	B	0.5	0.2	0.33	[0.25:0.40]
STRUCTURAL PARAMETERS						
Consumption aversion	σ_C	G	1.5	0.37	1.34	[1.15:1.47]
Consumption habits	h	B	0.7	0.10	0.42	[0.37:0.47]
Price adjustment cost sector N	κ_N	G	50	7.5	39.47	[33.51:44.94]
Price adjustment cost sector A	κ_A	G	50	7.5	59.14	[48.07:66.77]
Price indexation sector N	ξ_N	B	0.5	0.15	0.25	[0.15:0.31]
Price indexation sector A	ξ_A	B	0.5	0.15	0.23	[0.11:0.29]
Policy rule smoothing	ρ	B	0.8	0.05	0.76	[0.73:0.79]
Policy weight - inflation	ϕ_π	G	2	0.25	2.49	[2.27:2.69]
Policy weight - output growth	$\phi_{\Delta y}$	N	0.15	0.05	0.10	[0.08:0.12]
Policy weight - real exchange rate	ϕ_E	N	0.15	0.05	0.02	[0.01:0.02]
Consumption substitution	μ_C	G	10	5	2.20	[1.78:2.64]
Climatic damage - inertia	ρ_d	B	0.5	0.2	0.98	[0.97:0.99]
Climatic damage - output	γ_0^X	N	0	50	-45.15	[-63.37:-26.78]
Climatic damage - output (lag)	γ_1^X	N	0	50	9.51	[-2.13:22.76]
Climatic damage - cost	γ_0^Z	N	0	50	-20.96	[-29.83:-13.08]
Climatic damage - cost (lag)	γ_1^Z	N	0	50	9.16	[3.65:15.23]
Marginal log-likelihood					-1123.46	

Notes: The column entitled "Shape" indicates the prior distributions using the following acronyms: N describes a Normal distribution, G a gamma one, B a beta one, and IG an inverse gamma one.

weaker competition making prices stickier. In addition, we find that monetary policymaking had been more oriented toward inflation stabilization in New Zealand than in the US economy. For real exchange rate targeting, we obtain a value that lies in the ballpark of estimates obtained from the open economy monetary policy rule literature of Clarida et al. (1998) (they find ϕ_E=0.07 for G7 economies). Turning to the damage parameters, we find that the weather shocks have a strong negative immediate effect on agricultural output (γ_0^X<0) and depress demand for intermediate goods (γ_0^Z<0). However, the damage fuels demand for intermediate goods one period after the realization of the climate shock (with γ_1^Z>0) and generates inflation pressures in both sectors. This lag in the response after damage, modeled by γ_1^X, γ_1^Z>0, is explained by the observed dynamic of agricultural prices, which adjusts to weather shocks after one period. Finally, we find that the damage process is very inertial (with ρ_d=0.98), and this

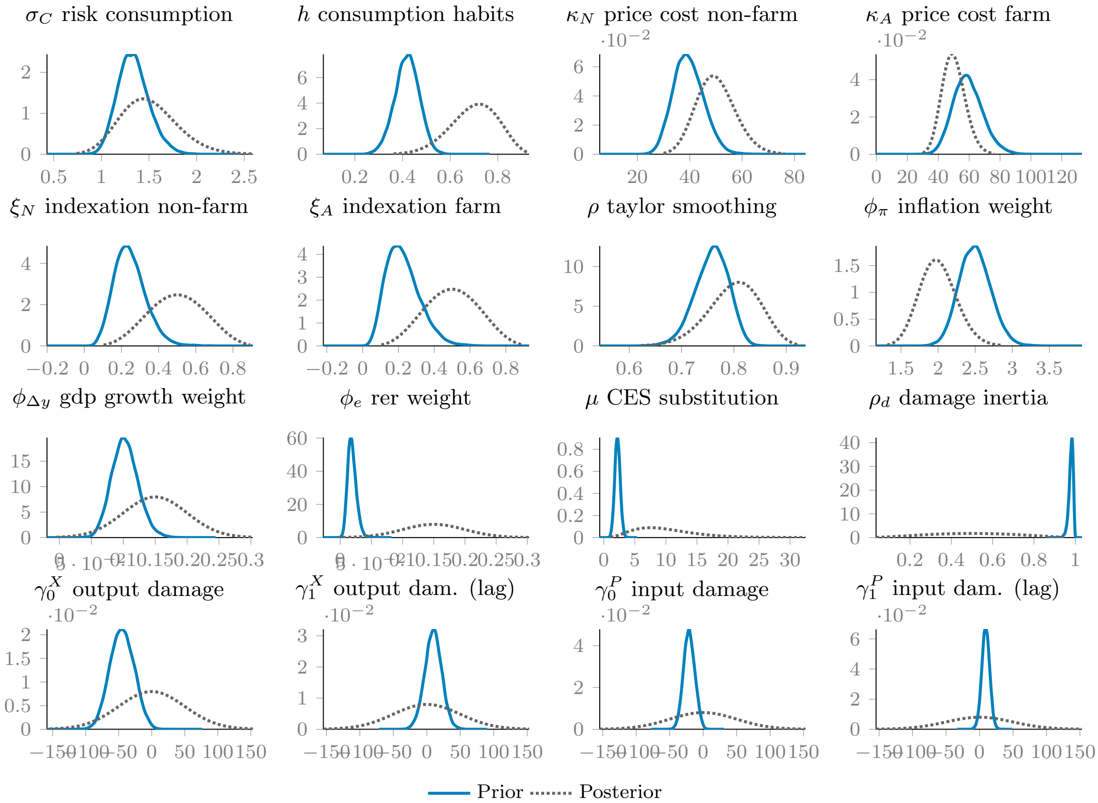


FIGURE 4.1: Prior and Posterior Distributions of Structural Parameters for New Zealand (Excluding Shocks)

results is consistent with the findings of Kamber et al. (2013). These authors find, using a long-run VAR for New Zealand, that drought shocks have persistent feedback effects on inflation and output. This pattern of weather-driven business cycles is captured here by ρ_d. The estimated standard deviation of surprise weather shocks is much larger than anticipated weather shocks, thus showing that unanticipated weather shocks play a larger role in the business cycle.

3.3 Do Weather Shocks Matter?

A natural question to ask at this stage is whether weather shocks significantly explain part of the business cycle. More broadly, it is also relevant to question whether the number of lags for the damage functions $\Gamma_Z(\cdot)$ and $\Gamma_X(\cdot)$ are consistent with data. To that aim, we consider four (nested) models $\mathcal{M}_q(\theta)$ differing from the functional forms of the weather costs. Each model is given by:

$$\mathcal{M}_q(\theta) = \begin{cases} \Gamma_s(\cdot) = 1 & \text{for } q = 0 \\ \Gamma_s(\cdot) = 1 + \sum_1^q \gamma_{q-1}^s d_{t+1-q} & \text{for } q > 0 \end{cases}, \quad s = \{X, Z\}, \tag{4.40}$$

TABLE 4.2: Prior and Posterior Model Probabilities

	No damage $\mathcal{M}_0(\theta)$	Damage $\mathcal{M}_1(\theta)$	Damage (+1 lag) $\mathcal{M}_2(\theta)$	Damage (+2 lags) $\mathcal{M}_3(\theta)$
Prior probability	1/4	1/4	1/4	1/4
Laplace approximation	-1125.30	-1128.59	-1123.45	-1126.98
Posterior odds ratio	1.00	0.037	6.341	0.186
Posterior model probability	0.132	0.005	0.838	0.025

where θ is the vector of the estimated parameters of the model $\mathcal{M}_q(\theta)$. We focus on four different versions of the model for $q = \{0, 1, 2, 3\}$. $\mathcal{M}_0(\theta)$ denotes the version of the model without damages (*i.e.*, weather variations do not incur macroeconomic fluctuations). The second model $\mathcal{M}_1(\theta)$ is a version where contemporaneous weather shocks generate fluctuations. The third version of the model $\mathcal{M}_2(\theta)$ is the version previously presented in the study with a damage function including one lag. Finally, the last version $\mathcal{M}_3(\theta)$ includes an additional lag.

We estimate these four versions of the model (using the same data and priors). Table 4.2 reports for four different nested models the corresponding data density (Laplace approximation), posterior odds ratio and posteriors model probabilities, which allow us to determine the model that best fits the data from a statistical standpoint. Using an uninformative prior distribution over models, we compute both posterior odds ratios and model probabilities taking the model $\mathcal{M}_0(\theta)$ without damages as the benchmark.[21] We conduct a formal comparison between models and refer toGeweke (1999) for a presentation of the method to perform the standard Bayesian model comparison employed in table 4.2 for our four models. Briefly, one should favor a model whose data density, posterior odds ratios and model probability are the highest compared to other models.

Contrasting the results of our four models, we find that the model $\mathcal{M}_2(\theta)$ employed in the present study is preferred to any other model, as its posterior probability is 83.8%. The result is confirmed in terms of the data density and posterior odds ratio. This result highlights that weather shocks play an important role in explaining macroeconomic fluctuations over the sample period. In addition, the lag number of the cost function ($q = 2$) employed in the present study is preferred to any other tested lag structure (q=1 or 3).

[21] As underlined by Rabanal (2007), it is important to stress that the marginal likelihood already takes into account that the size of the parameter space for different models can be different. Hence, more complicated models will not necessarily rank better than simpler models, and $\mathcal{M}_3(\theta)$ will not inevitably be favored to other models.

Similarly, we have applied the same standard Bayesian model comparison applied to weather news shocks in order to examine whether farmers are able to anticipate weather shocks before their realization.[22] Estimating different versions of the model where farmers anticipate a weather shock one, two or eight periods in advance, we find that anticipated weather shocks account for a very small fraction of weather fluctuations ($< 1\%$) and, more broadly, of business cycle fluctuations. Thereby, this result shows that farmers are not able to anticipate weather shocks.

4 Weather Shocks as Drivers of Business Cycles

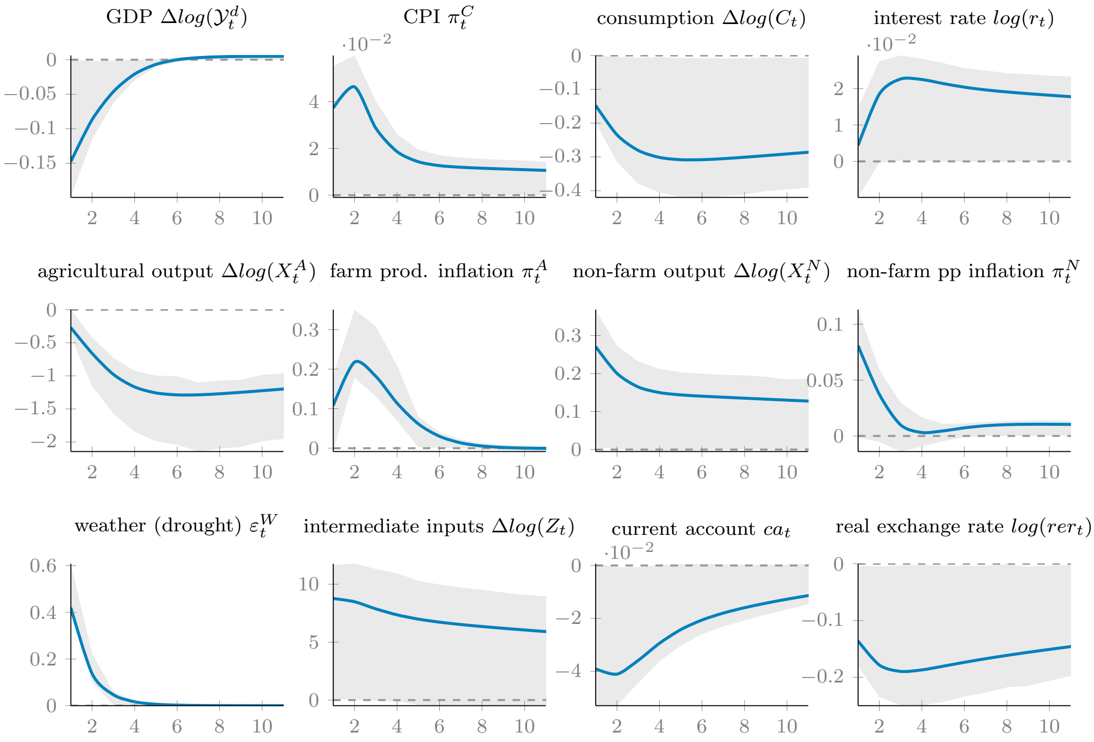
This section discusses the propagation of a weather shock and its implications in terms of business cycle statistics.

4.1 Propagation of a Weather Shock

In the model, the measure of drought is assumed to be a stochastic exogenous process driven by two shocks: a standard surprise shock (η_t^W) and an anticipated one ($\tilde{\eta}_{t-1}^W$), which we to refer as the weather news shock. The insight behind the weather news shock is that farmers may be able to anticipate weather variations one quarter before they occurs. To evaluate how an average drought event in New Zealand propagates in the economy, we first report the simulated Bayesian system responses of the main macroeconomic variables following a standard weather shock in fig. 4.2 and a weather news shock in fig. 4.3. The impulse response functions (IRFs) and their 90% highest posterior density intervals are obtained in a standard way when parameters are drawn from the posterior distribution, as reported in fig. 4.1.

A drought event strongly affects business cycles through a large decline in agricultural output, as weather is a direct input in the production process of agricultural goods. This result is in line with Kamber et al. (2013), as New Zealand's farmers rely extensively on rainfall to support the agricultural sector. This shock acts as a standard negative supply shock through a combination of rising prices and falling output. The damages incurred by the weather shock to agricultural output are rather persistent, as output requires more than 10 periods to return to the steady state. This persistence can be explained by the deterioration of the competitiveness of farmers on international commodity markets, and thus, they require time to recover their market share.

[22] Formally, in the weather shock process, a shock anticipated Q quarters in advance is given by: $\sum_{q=1}^{Q} \tilde{\eta}_{t-q}^W$.

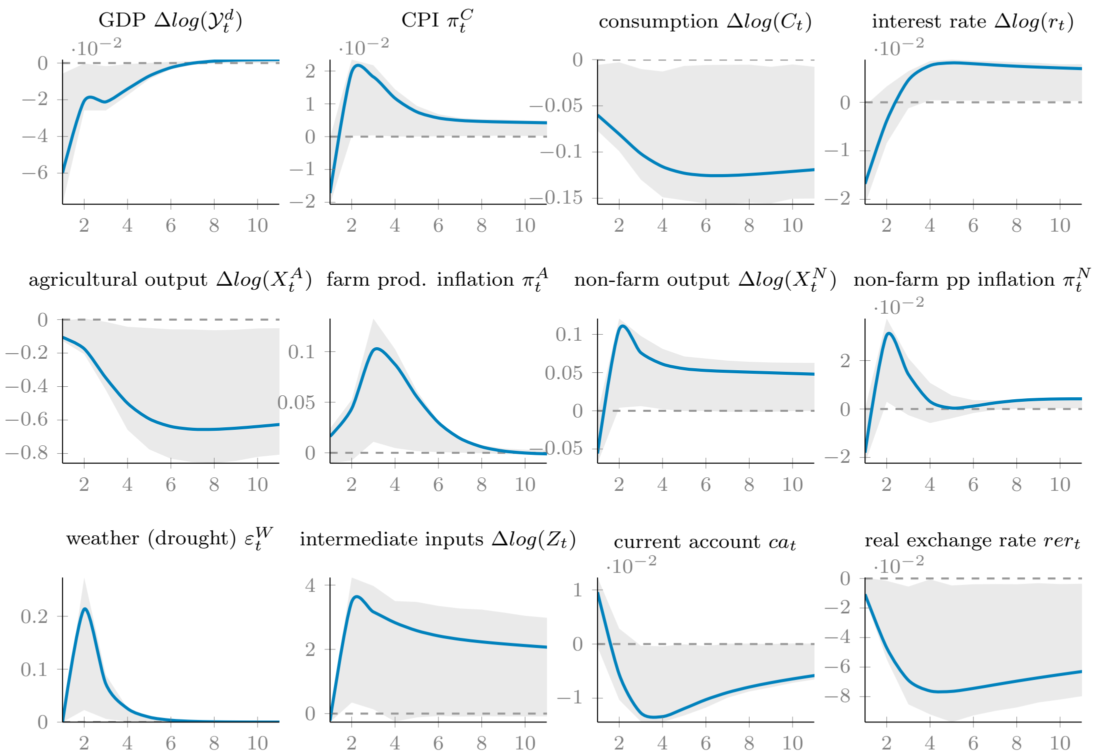


Notes: Blue lines are the medians of the distributions of the Impulse Response Functions (IRFs) generated when parameters are drawn from the posterior distribution, as reported in fig. 4.1. Grey areas are the 90 percent highest posterior density interval. IRFs are reported in percentage deviations from the deterministic steady state. "pp" stands for producer price.

FIGURE 4.2: System Response to an Estimated Weather Shock η_t^S Measured in Percentage Deviations from the Steady State

In reaction to inflation pressures, the central bank increases its nominal interest rate, which deteriorates consumption and output. Monetary policy tightening combined with a decline in real agricultural production depresses aggregate GDP growth for four periods before returning to equilibrium.

A drought shock increases the feed budget, since dairy cattle require more water as temperature, humidity, and production levels rise. In extreme cases, farmers might even be forced to slaughter their cattle. Farming activities also require more water to irrigate lands to offset the soil dryness. This demand effect in terms of intermediate inputs is captured by our model through the increase of 8% in intermediate inputs (Z_t), which has a positive side effect on non-farm output (X_t^N). Regarding international economics, the decline in domestic agricultural production generates current accounts deficits. Two factors might explain this. First, a substantial part of New Zealand's exports is accounted for by agricultural commodities. As agricultural output is depressed, this might also negatively affect exports. Second, the need for intermediate goods might be such that it increases imports. These two mechanisms lead to a deterioration in the current account. In the meantime, the real exchange rate depreciates driven by the depressed competitiveness of farmers.



Notes: Blue lines are the medians of the distributions of the Impulse Response Functions (IRFs) generated when parameters are drawn from the posterior distribution as reported in fig. 4.1. Grey areas are the 90 percent highest posterior density intervals. IRFs are reported as percentage deviations from the deterministic steady state. "pp" stands for producer price.

FIGURE 4.3: System Response to an Estimated Weather News Shock $\hat{\eta}_{t-1}^W$ Measured as Percentage Deviations from Steady State

Turning to the weather news shock, *i.e.*, the one farmers might anticipate one period before it occurs, the transmission mechanism is quite similar to the weather surprise shock overall, with declining output and increasing inflation. Anticipating a shock one quarter in advance, farmers decide to reduce their production to avoid losses due to poor weather conditions. The market reacts to this decline in agricultural output by adjusting prices. Firms operating in the non-agricultural sector anticipate a recession and reduce their production in advance, which causes non-agricultural prices and interest rates to drop.

Overall, a representative weather shock has a clear depressing effect on both agricultural output and aggregate GDP. Our model identifies the weather shock as a negative productivity shock, characterized by a large and durable decline in output and an increase in inflation.

4.2 The Contributions of Weather Shocks on Aggregate Fluctuations

Figure 4.4 reports the forecast error variance decomposition for the four variables of interest, *i.e.*, aggregate production ($\mathcal{Y}_t^S$), real domestic absorption ($\mathcal{Y}_t^D$), agricultural production (X_t^A) and agricultural prices (π_t^A). Five different time horizons are considered, ranging from one quarter ($Q1$) to ten years ($Q4$) along with the unconditional forecast error variance decomposition ($Q\infty$). In each case, the variance is decomposed into five main components related to supply shocks (technology and markup shocks), demand shocks (preference and monetary policy shocks), foreign price shocks, foreign demand shocks and weather shocks.

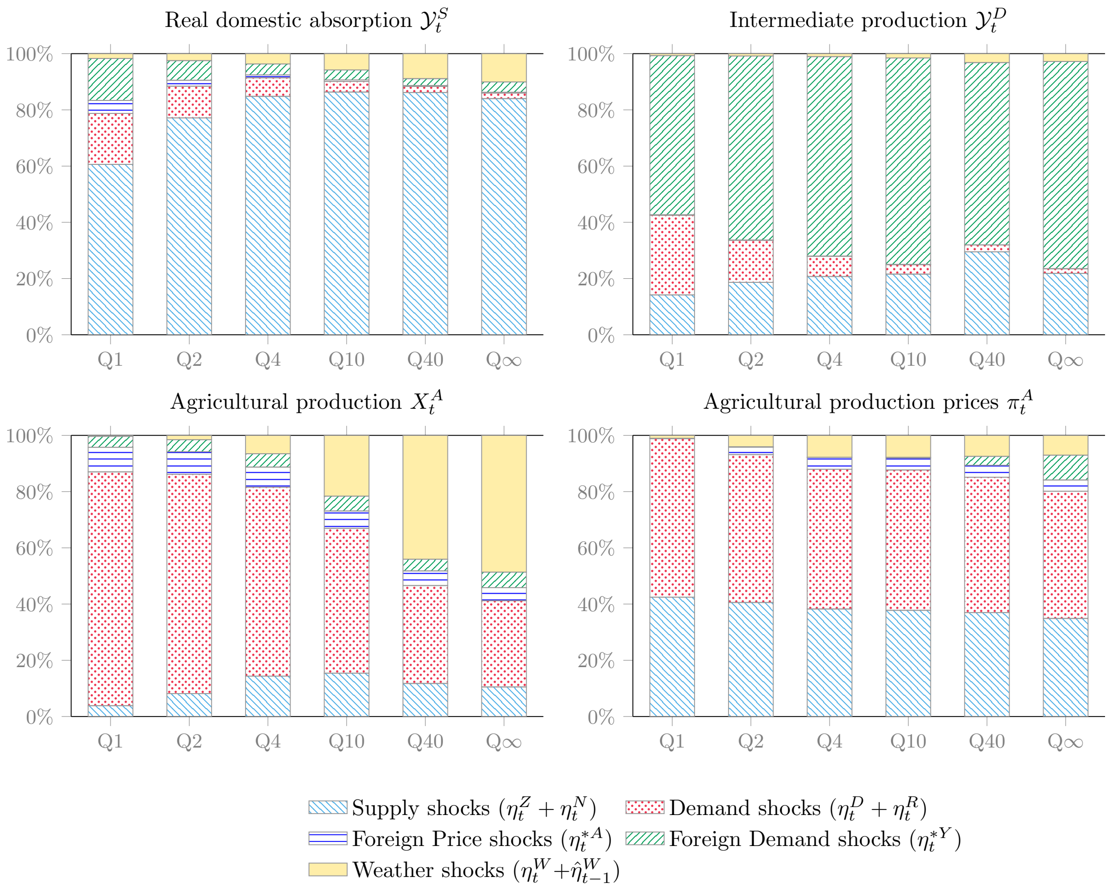


Figure 4.4: Forecast Error Variance Decomposition at the Posterior Mean for Different Time Horizons (one, two, four, ten, forty and unconditional).

As observed for aggregate production ($\mathcal{Y}_t^S$), home and foreign demand shocks are the main drivers of the variance in the very short run. However, by increasing the time horizon, supply and weather shocks become the leading forces of production cycles to the detriment of demand shocks. In the long run, the unconditional variance error forecast decomposition shows that weather shocks explains up to 9% of New Zealand's production.

For the total demand ($\mathcal{Y}_t^D$), unsurprisingly, demand shocks are the main drivers of fluctuations with a predominance of foreign demand shocks regardless of time horizon. Both types of shocks account for 84% of fluctuations on a one-quarter horizon and up to 93% on a forty-quarter horizon. In contrast to the aggregate production, the contribution of weather shocks to macroeconomic fluctuations is quite modest, although increasing over time.

Turning to agricultural output, demand shocks account for most fluctuations in the short run, while their importance declines in the long run, although remaining non-negligible. Weather shocks remarkably drive the variance of agricultural output, and increasing the time horizon magnifies this result in a similar fashion to the aggregate production.

Conversely, for agricultural prices, the variance of the forecast error is almost entirely explained by both supply and demand shocks, which combined represent 98% of the fluctuations in agricultural prices in the very short run and a slightly lower share in the long run: 84% at a ten-year horizon. Interestingly, the importance of weather shocks is also growing with time. However, agricultural prices are mainly driven by foreign shocks. This result is quite consistent with empirical evidence showing that food prices are internationally determined.

Overall, we find that weather variations cause important macroeconomic fluctuations, especially in the long run because of the estimated inertia of the damage function. The prospect of the increasing variance of drought events caused by climate change is a challenging issue for New Zealand policymakers, as it can have large implications for stabilizing policies.

4.3 Historical Decomposition of Business Cycles

An important question one can ask of the estimated model is how important the weather shocks were in shaping the recent New Zealand macroeconomic experience. Figure 4.5 provides an answer by reporting the time paths of aggregate output, agricultural production and production prices on a quarter-to-quarter basis. The solid line depicts the time path of the ratio of deviation from the steady state, while the bars depict the contribution of the shocks (gathered by groups) in the corresponding point deviation (at the mean of the estimated parameters).

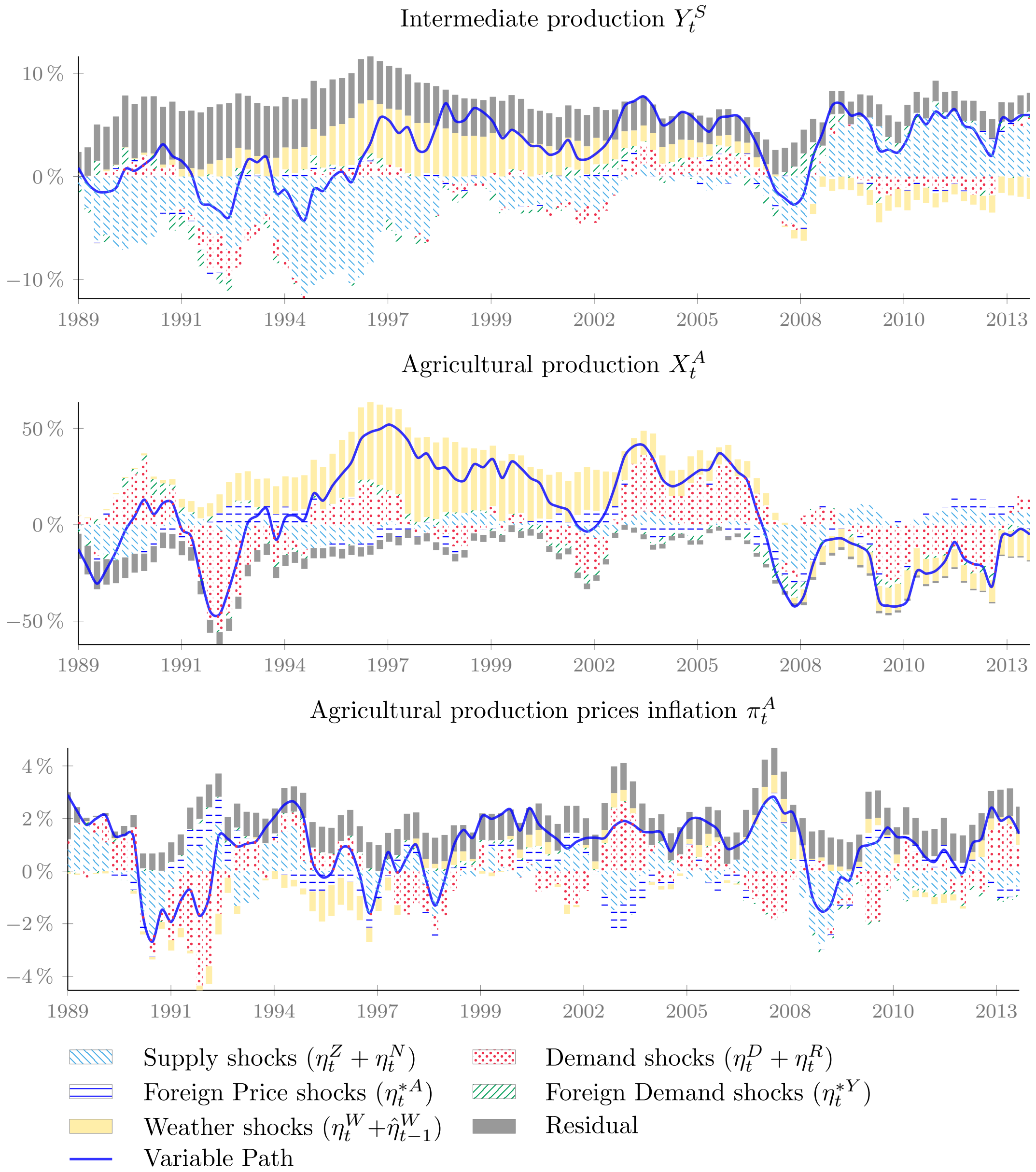


FIGURE 4.5: Historical Decomposition of Aggregate Output, Agricultural Production and Agricultural Production Price Inflation

In fig. 4.5, we can distinguish between two time periods for output, $(\mathcal{Y}_t^S)$ and (X_t^A). First, up to 2006-2007, variations in aggregate production positively entailed weather shocks. Over this period, New Zealand did not experience any significant drought events, with important soil moisture surpluses favoring agricultural production and decreasing production prices (π_t^A). In fact, during this period, approximately two-thirds of the increase in agricultural output was driven mostly by positive weather shocks.

However, major drought events in 2008, 2010 and 2013 contributed negatively to output fluctuations accompanied by an important inflation increase that cleared the imbalances in the market for agricultural goods. After 2008, almost one-third of the decline in agricultural output is driven by adverse weather drought shocks. Regarding production price inflation, weather shocks have a limited impact on fluctuations over the sample period. We find that agricultural prices are mainly driven by home and international demand shocks, as underlined by the previous forecast variance error decomposition analysis.

4.4 Climate Change Implications for Aggregate Fluctuations

We now turn to the implications of climate change for aggregate fluctuations. The IPCC defines climate change as "*a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*" (Edenhofer et al., 2014). In our framework, climate is supposed to be stationary, which makes our set-up irrelevant for analyzing changes in mean climate values. However, it allows for changes in the variance of climate. As a first step, we assess the change in the variance of the weather shock by estimating it under different climate scenarios. Then, in a second step, we use the estimates of these variances for each scenario and investigate the effects on aggregate fluctuations.

4.4.1 Building Projections on Climate Shocks Variance

To investigate the potential impact of climate change on aggregate fluctuations, we assume that the volatility of climatic shocks (η_t^W and $\hat{\eta}_{t-1}^W$) (eq. (4.13)) will be affected by climate change. Instead of arbitrarily setting a value for this shift, we provide an approximation using a proxy for the drought index. To do so, we rely on monthly climatic data simulated from a circulation climate model, the Community Climate System Model (CCSM). The resolution of the dataset is a $0.9° \times 1.25°$ grid. Simulated data are divided into two sets: one of "historical" data up to 2005 and one of "projected" data from 2006 to 2100. The projected data are given for four scenarios of greenhouse gas concentration trajectories, the so-called Representative Concentration Pathways

(RCPs). The first three, *i.e.*, the RCPs of 2.6, 4.5 and 6.0, are characterized by increasing greenhouse gas concentrations, which peak and then decline. The date of this peak varies among scenarios: around 2020 for the RCP 2.6 scenario, around 2040 for the RCP 4.5 and around 2080 for the RCP 6.0. The last scenario, the doom and gloom 8.5 pathway, is based on a quickly increasing concentration over the whole century.

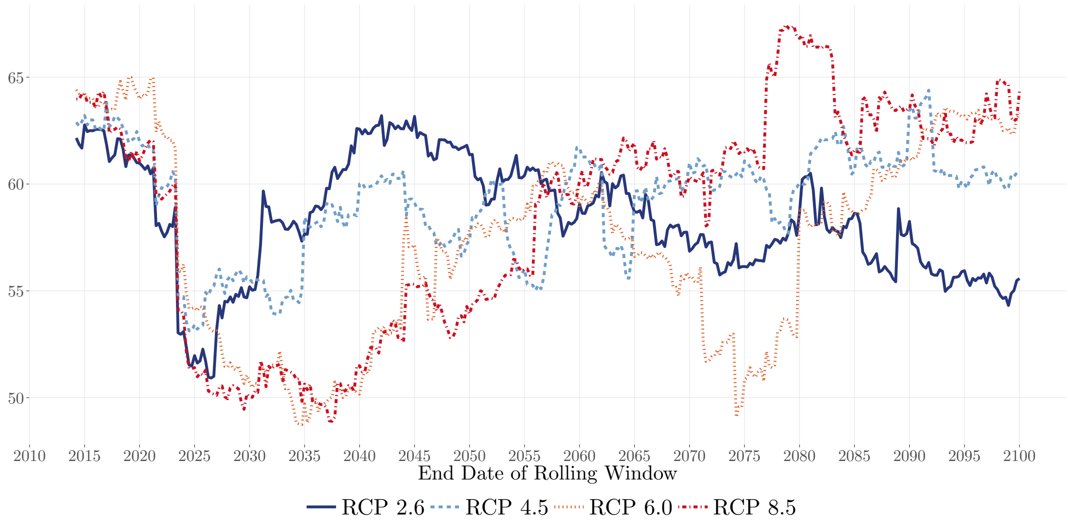
For these four scenarios, soil moisture deficit data are not available. We therefore use a strongly correlated variable as a proxy: total rainfall. Simulated data for each scenario are provided on a grid on a monthly basis. We aggregate them at the national level on a quarterly basis. More details on the aggregation can be found in appendix 1.

These data are then used to estimate the evolution of the volatility of the climatic shock. We do so using a rolling window approach. In the DSGE model, we assume that the weather shock is autoregressive of order one. We therefore fit an $AR(1)$ model on each window. The size of the latter is set to 25.5 years, *i.e.*, the length of the sample data used in the DSGE model, so each regression is estimated using 102 observations. The standard error of the residuals are then extracted to give a measure of the evolution of the volatility of the climatic shock. Figure 4.6 illustrates them for each scenario. It is then possible to compute the average growth rate of the standard error over the century depending on the climate scenario.[23] In the best-case scenario, RCP 2.5, the variance of the climate measure is reduced by 5.29%; under the RCP 4.5 and RCP 6.0 scenarios, it increases by 5.34% and 6.42%, respectively; under the pessimistic RCP 8.5 scenario, it drastically increases by 20.46%.

4.4.2 Measuring Climate Change Implications for Aggregate Fluctuations

We use the estimated DSGE model to assess the effects of a shift in the variability of the weather shock process. We do so in a two-step procedure. First, the simulations are estimated with the value of the standard error of the weather shock that is estimated during the fit exercise, which corresponds to historical variability. Second, new simulations are made after altering the variability of the weather shock so it corresponds to the one associated with climate change, using the values obtained from the previous section. Hence, we proceed to four different alterations of the variance of the weather process.

[23] More details on the procedure can be found in appendix 1.



Notes: Each curve represents the standard errors of climate shock resulting from the rolling window estimation of an $AR(1)$ model using data from the 25.5 previous years for a Representative Concentration Pathways scenario.

FIGURE 4.6: Estimations of the Standard Error of Climatic Shock Under Four Different Climate Scenarios

TABLE 4.3: Changes in Standard-Errors of Simulated Observables Under Climate Change Scenarios

	1989-2014	2015-2100 (projections)			
	Benchmark	RCP 2.5	RCP 4.5	RCP 6.0	RCP 8.5
sd(η_t^W)	100	94.71	105.34	106.42	120.46
sd($\mathcal{Y}_t^S$)	100	99.57	100.68	100.93	102.37
sd($\mathcal{Y}_t^D$)	100	99.88	100.19	100.26	100.66
sd(X_t^A)	100	97.92	103.27	104.50	111.47
sd(π_t^A)	100	98.37	102.57	103.53	109.00
sd(C_t)	100	99.88	100.19	100.26	100.66
sd(r_t)	100	99.96	100.06	100.09	100.23
sd(rer_t)	100	99.97	100.04	100.06	100.15

Notes: The model is first simulated as described in section 3. Theoretical standard errors of each variable are then estimated and normalized to 100. Then, standard errors of both weather (η_t^W) and weather-news shocks ($\tilde{\eta}_t^W$) are modified to reflect different climate scenarios (compared to the reference 1986–2014 period, changes in the standard error are as follows: RCP 2.5, -5.29%; RCP 4.5, $+5.34\%$; RCP 6.0, $+6.42\%$; RCP 8.5, $+20.46\%$). New simulations are estimated using the modified standard errors of these shocks, and the theoretical standard errors of the variables of interest are then compared to those of the reference period. The variables of interest are aggregate production ($\mathcal{Y}_t^S$), total demand ($\mathcal{Y}_t^D$), agricultural production (X_t), agricultural prices (π_t^A), consumption (C_t), interest rate (r), and real exchange rate (rer_t).

To measure the implications of climate change on aggregate fluctuations of a representative open economy, we compare the volatility of some macroeconomic variables under historical weather conditions (for the 1989–2014 period) to their volatility under future climate scenarios (for the 2015–2100 period), normalizing the values of the historical period of each variable to 100.

Table 4.3 reports these variations for some key variables. The first scenario is clearly optimistic, as the standard deviation of drought events is declining by 5.29%. Macroeconomic fluctuations are clearly affected by the concrete reduction of the volatility of outputs and prices for New Zealand, ranging from roughly -0.1% to -2%. In contrast, we consider two intermediate pessimistic scenarios characterized by weather shock volatility rising between 5% and 6% (RCPs 4.5 and 6.0). For these scenarios, our model predicts a strong increase in the standard deviations of macroeconomic variables. In particular, the standard deviation of agricultural output increases by 4.5% and that of agricultural prices by 3.53%. Finally, in the worst-case scenario (RCP 8.5), a 20.46% increase in the standard deviation of weather shocks has important implications for the business cycles of New Zealand. It leads agricultural output variability to rise by 11% and inflation to rise by 9%, and it affects the variability of aggregate production by 2%.

5 Conclusion

In this chapter, we have investigated the business cycle evidence on weather shocks. We have developed and estimated a DSGE model for a small open economy, New Zealand. Our model includes an agricultural sector that faces an exogenous weather input affecting the production function and demand for the intermediate goods. Using our estimated model, we find that weather shocks play an important role in explaining macroeconomic fluctuations over the sample period. This finding is robust to different specifications of the lag structure of the damage function affecting agricultural production. However, our framework shows that farmers do not anticipate weather shocks and are mostly surprised by variable climatic conditions. Our results also show that in the medium run, weather shocks are important drivers of agricultural production and are responsible for variations in agricultural prices and total output. These findings suggest that weather shocks should not be neglected in the conduct of macroeconomic policies, especially since one-third of the decline in agricultural output after 2008 is driven by adverse weather drought shocks, as illustrated by our historical decomposition of business cycles. Finally, our framework is amenable to the analysis of climate change. Our simulations show that altering the variability of weather shocks in line with what is expected to happen with climate change leads to an increase in the variability of key macroeconomic variables, such as output prices, production or inflation, in all but the most optimistic scenario.

The analysis of weather-driven business cycles is a burgeoning research area given the important context of climate change. In this chapter, we have analysed the importance of weather shocks on the macroeconomic fluctuations of a developed economy. However, the application of our framework to developing countries could highlight the high vulnerability of their primary sectors to weather shocks. In addition, from a policymaker's perspective, our framework could be fruitfully employed to evaluate the optimal conduct of monetary, fiscal and environmental investment policies to mitigate the destabilizing effects of weather shocks for different scenarios of climate change.

General Conclusion

Scientists predict that climate change will result in an increase of the average temperature accompanied by more severe weather events, such as drought and desertification, intense rainfall, flooding, etc. As the list of potentially harming events goes on and on, so does the need for documentation on their effects on our planet. The aim of this thesis is to contribute to this effort by focusing on a specific area, agriculture. Many challenges lay ahead with respect to climate change. The last 2015 Paris international climate agreement, signed by 175 parties, sets goals to keep a global temperature rise well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit it to 1.5 degree Celsius. It is however up to the respective governments to take action to achieve this ambitious goal, with no incentive to prevent the free rider problem from occurring. In any case, whether the goal of the limiting temperature is reached or not, even an increase of 1.5 degree Celsius above the pre-industrial level is expected to significantly affect agriculture. The impacts are expected to affect developing and developed countries differently. In developing countries, although the process of catching up to the developed countries mitigates the importance of agriculture in the economy, this sector still represents a relatively important part of total output and provides jobs to millions of people. Hence, threats posed by climate change on agriculture are likely to have substantial consequences on production, and therefore on profits and on food security. These problems also apply to developed countries, even if their economy depends less on agriculture. In fact, a large part of the global production comes from developed countries. On the basis of the estimates of the FAO, around 40% of global cereal production comes from developed countries at this time. Such a large share implies that the impact of climate change on developing countries should not be overlooked. Both for developing and developed countries, adverse weather accidents might drastically reduce production resulting in disastrous situations of food shortage, as witnessed during the last decades. A better understanding on the underlying mechanisms is therefore necessary to help mitigate the harmful effects of climate change, to be able to feed the growing population of our planet.

The four chapters of this thesis are an attempt to provide some insight into these challenges. The first part focuses on developing countries and provides two empirical studies based on Indian data at the individual farm level. The second part considers developed countries with a first look at crop yields in Europe followed by an analysis of weather shocks on business cycles.

The main results can be summarised as follows. The empirical studies provided in chapters 1 and 2 show heterogeneous impacts of climate on profits, on production, and on consumption choices in India. The agricultural production of some farmers as well as their profits is projected to increase under the climate scenarios tested. But these gains are more than offset by the losses projected for the other farmers, so that the overall projected effect of climate change is damaging to Indian agriculture. Furthermore, climate change scenarios underscore a contrasting difference between the north and the south of the country, the former being more vulnerable to the scenarios considered. Some farming practices however enable farmers to better cope with changing climate conditions. Irrigated farms tend to be less affected by a marginal change in temperature and in total precipitation. As around 40% of Indian farms still rely on water from precipitation only to irrigate crops, further efforts can be made to improve irrigation schemes. Mixing crops is another possible way of mitigating the overall damaging effects of climate change, especially for small farms.

The relationship between the weather and crop yields in Europe is investigated in Chapter 3. Wheat yields tend to rise under the projected climate scenarios in southern Europe, although this rise is accompanied by a relatively high variability. In the northern regions, *i.e.*, in regions in which wheat production is currently relatively higher, small gains are projected, but also accompanied by a lot of variability. Projections for corn yields are more pessimistic. In the short-run, small gains are projected, but in the long-run, these gains turn to relatively high losses, especially for southern regions.

Finally, the DSGE model presented in chapter 4 stresses the role of the weather in explaining the impact of weather shocks in the short-run of macroeconomic fluctuations. The model is developed for a small-open economy with two sectors, one of which – the agricultural sector – being affected by a weather shock, more specifically, by a drought. The model identifies the weather shock as a negative supply shock that depresses both GDP and agricultural production, followed by a rise in prices. The potential effects of climate change are addressed by altering the variance of the weather shock process, depending on different climate scenarios. The results show that the modification in the variability of the weather shock leads to an increase in the variability of key macroeconomic variables such as output prices, production or inflation, in all but the most optimistic scenario.

Looking forward, some efforts could be directed towards several points for further research. The analyses on the impacts of climate on profits could be extended to a wider geographical area, to provide a more complete picture. The production and consumption decisions of rural households could also be further documented, using a framework modelling these two decisions in a single model, to account for market imperfections. Some more research could also be done regarding the short-run impacts of weather shocks on the economy. For example, it might be interesting to delving deeper into the empirical facts, by developing in more details a VAR-type model. Focusing on the welfare aspect of the question might also be a starting point for further work. Finally, the literature finds evidence that developing countries are and will be more vulnerable to climate change than developed countries. However, some disparities are also observed within countries. Hence, it may be interesting to investigate how climate change can affect social inequalities.

Appendix A

Ricardian Analysis: Data

1 Definitions of Variables

Table A.1 provides a definition of each variable used in the analysis.

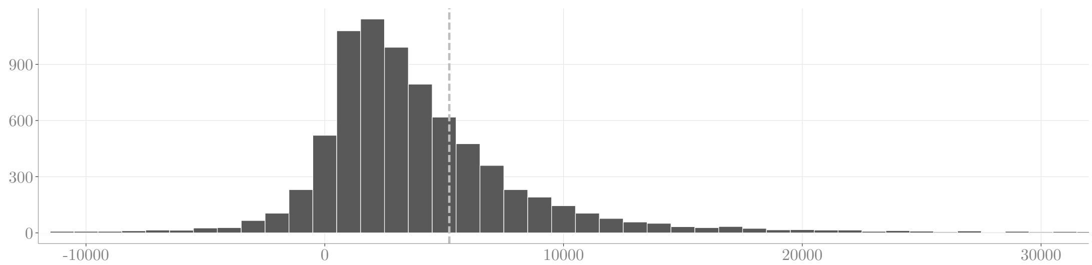
Table A.1: Description of Variables

Variable	Description	Type
Variable of interest		
Net ag. revenue	Net agricultural revenue (rupees)	numeric
Personal characteristics		
Age of head of household	age of the head of the household	numeric
Literacy	Years of schooling ($\in [0, 15]$)	numeric
Farm characteristics		
Area planted	Planted surface (acres)	numeric
No. bullock carts	Number of bullock carts	numeric
No. tractors	Number of tractors	numeric
No. different cultures	Number of different cultures	numeric
No. workers in the farm	Number of workers in the farm	numeric
Irrigation	Most important type of irrigation (none, tube well, other well, government, tank, private canal, other)	factor
Location		
Latitude	Latitude (degrees)	numeric

Continued on next page

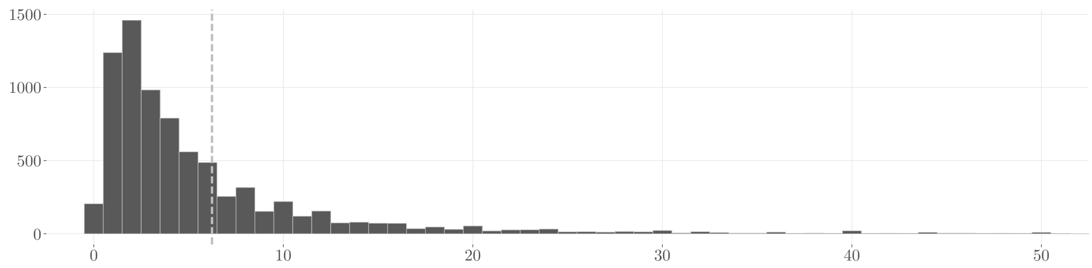
Variable	Description	Type
Pop. density	Population density (number of inhabitants per square meter)	numeric
Climatic factors		
Winter precip.	January to March total rainfall average (mm)	numeric
Summer precip.	April to June total rainfall average (mm)	numeric
Monsoom precip.	July to September total rainfall average (mm)	numeric
Autumn precip.	October to December total rainfall average (mm)	numeric
Winter temp.	January to March mean temperature average	numeric
Summer temp.	April to June mean temperature average	numeric
Monsoom temp.	July to September mean temperature average	numeric
Autumn temp.	October to December mean temperature average	numeric

Figure A.1 shows the distribution of net revenues per acre, while Figure A.2 presents the distribution of cultivated area and fig. A.3 the distribution of irrigation types.



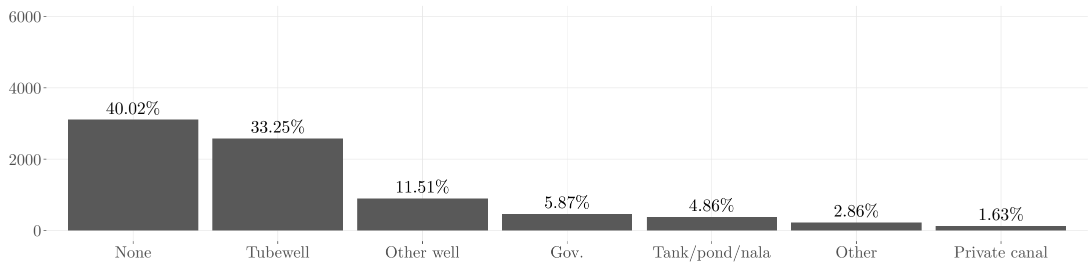
Note: the average value is represented by the dashed vertical grey line. The y-axis gives the number of farms in the sample in each bin.

FIGURE A.1: Net Revenues per Acre Distribution



Notes: the average value is represented by the dashed vertical grey line. The y-axis gives the number of farms in the sample in each bin.

FIGURE A.2: Cultivated Surface



Notes: The y-axis gives the number of farms in the sample for each type of irrigation.

FIGURE A.3: Most Important Mode of Irrigation (Number of Observations)

2 Weather Data

2.1 Observed Weather Data

This annex provides more details on the methods used to compute climate "normals" at the district level from weather station data. Figure A.4 summarizes the procedure. We rely on daily mean temperature and total rainfall data, provided by the National Climatic Data Center (NCDC)/National Oceanic and Atmospheric Administration (NOAA).

The first step consists in roughly estimating missing values. We follow a simple rule: if no more than 4 observations are missing, both during the previous and the next 14 days, the missing value is estimated by a weighted mean. Weights are computed in the following way:

$$w_i = \frac{d_i^2}{\sum_{j=1}^{n} d_j^2}, \tag{A.1}$$

where $d_i = (15 - i)\delta$, with $\delta = 1$ if the observation i days away is available, $\delta = 0$ otherwise. These weights give thereby more importance to close observations. As a result, we can rely on more observation (see fig. A.6) for the estimation in the following step.

The second consists in using the available data to make predictions where there is no station. The idea is to consider a grid covering India. For each cell of this grid, a prediction is made, using an interpolation method called *thin plate splines* (see *e.g.* Di Falco et al. (2011); Boer (2001); Hutchinson (1995)), implemented in the statistical software R in the package *fields* (Nychka et al., 2015). On average, there are 61 stations providing data for each day (see fig. A.6). The reliability of the estimation was assessed by cross-validation for each day, leaving one observation out and checking if the actual value lies in the confidence interval. The interpolation predicts 84.46% of actual weather station precipitation and 76.79% of actual weather station precipitation.[1]

Once the estimation for each cell of the grid is performed, an average by district can easily be computed. It is then possible to aggregate data by season and district. Results are displayed in figs. A.7 and A.8 for precipitation and precipitation, respectively.

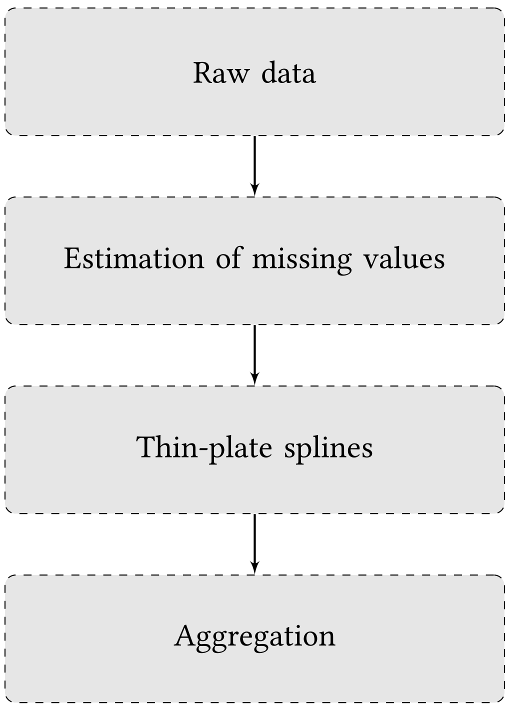
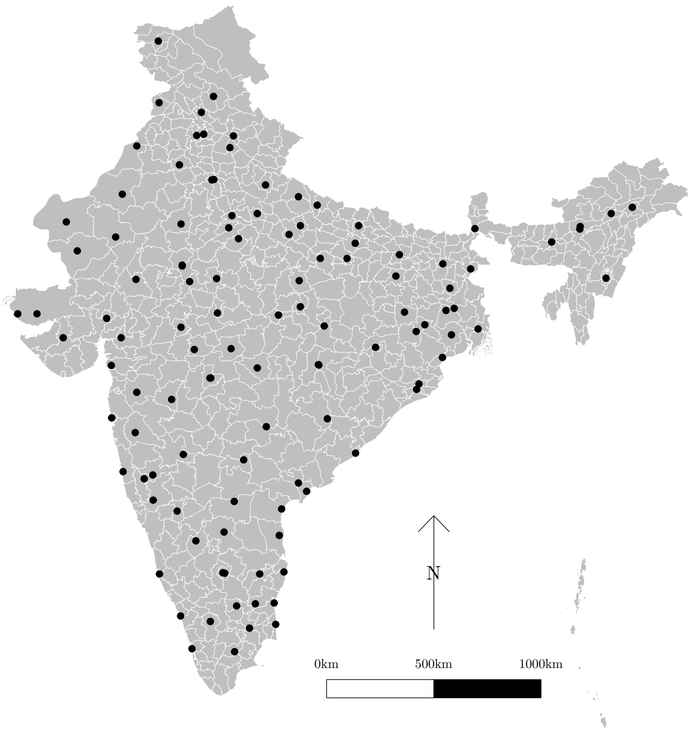


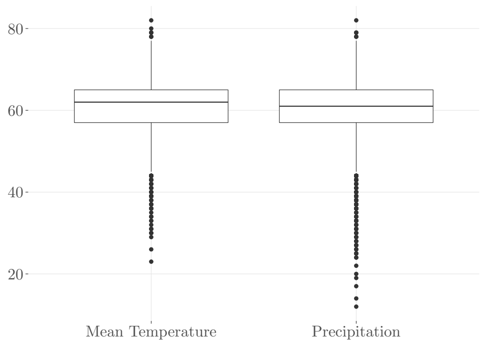
FIGURE A.4: Process from Raw Data to District Level Climatic Data

[1] A way to improve this accuracy would be to add elevation data to realize the interpolation.

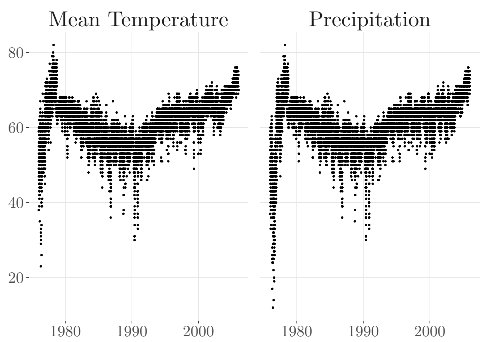


Notes: Each dot represents the location of a weather station.

Figure A.5: Meteorological Stations Locations in India



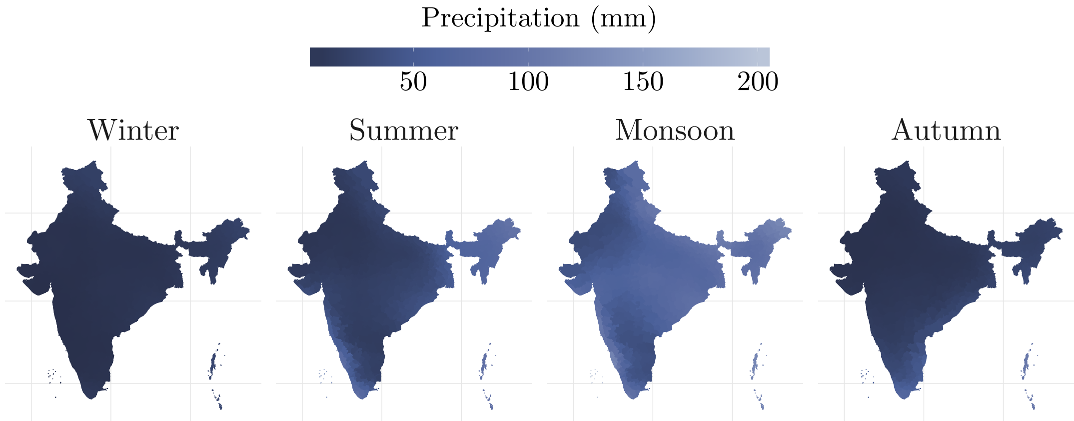
(a) Boxplot



(b) Overview

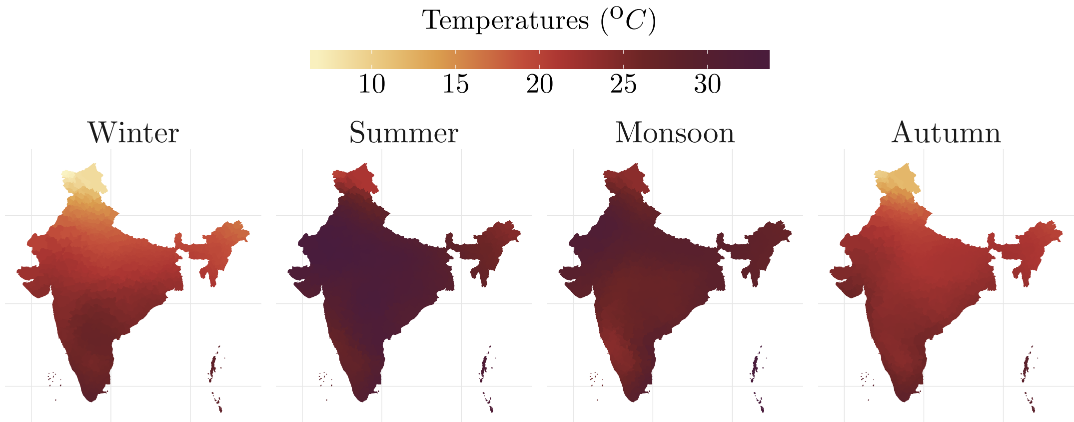
Notes: The distribution of the number of weather stations used to compute daily weather data is displayed on the left panel. The evolution through time of the number of weather stations used is displayed on the right panel.

Figure A.6: Number of Observations Used to Estimate Weather Data per Day



Notes: Precipitation “normals” correspond to 30-year average over the period ranging from 1976–2005.

Figure A.7: Precipitation “Normals”



Notes: Temperature “Normals” Correspond to 30-year Average Over the Period Ranging from 1976–2005.

Figure A.8: Temperature “Normals”

2.2 Climate Scenarios

To give an idea of the potential consequences of climate change on Indian net revenues, we envisage two climate scenarios and observe the changes in net revenues in each of them under the new weather conditions. To set up the scenarios, we follow Chaturvedi et al. (2012). The first scenario reflects a low concentration of greenhouse gas (roughly corresponding to the representative concentration pathway (RCP) 2.6, adopted by The Intergovernmental Panel on Climate Change for its fifth Assessment Reports in 2014), where average temperature for India is projected to increase by 1.7°C and total rainfall by 1.2%. It might be viewed ad a mitigation scenario. The second scenario reflects high concentration of greenhouse gas (roughly corresponding to the RCP 8.5), mean temperature is projected to increase by $2.02°C$ and total rainfall by 2.4%. This scenario is more pessimistic than the first.

Appendix B

Agricultural Yields: Data

1 Agricultural Data

The agricultural data are from the Farm Accountancy Data Network[1] (FADN). For statistical anonymity, the observations collected at the level of European farms are aggregated at the NUTS-3 geographic level. The NUTS-3 regions are subdivisions of the European territory established by Eurostat. All in all, the European Union is divided in $1,294$ economic territories, and the FADN data report values for 139 NUTS-3 regions in 28 countries, from 1989 to 2009.

Farm plots are classified according to their main activity, in 8 categories: (i) Fieldcrops, (ii) Horticulture, (iii) Wine, (iv) Other permanent crops, (v) Milk, (vi) Other grazing livestock, (vii) Granivores, ($viii$) Mixed. In our analysis, we focus on farms whose main activity is crop growing, *i.e.*, the first category in the dataset.

In the study, some restrictions are imposed on the dataset to ensure the convergence properties of the estimates. First, we only keep regions for which at least 15 observation are provided in the historical period ranging from 1989 to 2009.Then, we discard observations from isolated areas such as small islands.Then, we create two datasets, one for regions reporting values for wheat production, and the other one giving values for corn production. This leaves us with the following specifications:

- Wheat dataset: 545 observations in 31 NUTS-3 regions from 8 countries (Austria, France, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom)

[1] The FADN database is publiclu available at http://ec.europa.eu/agriculture/rica/database/consult_std_reports_en.cfm

  - 384 of which are located north of the 45^{th} parallel
  - 161 of which are located south of the 45^{th} parallel

- Corn dataset: 446 observations in 25 NUTS-3 regions from 5 countries (Austria, France, Italy, Portugal, Spain)
  - 284 of which are located north of the 45^{th} parallel
  - 162 of which are located south of the 45^{th} parallel

2 Weather Data

This section describes historical and projected weather data used in the main document.

2.1 Definitions

Weather data are obtained from the Meteorological Research couples ocean-atmosphere model MRI-CGCM3, and aggregated at regional level. Raw data are given at a daily frequency, on a $1.125° \times 1.12148°$ grid. We aggregate them at the NUTS-3 level by means of an area-weighted means, such that for each region, the aggregate value corresponds to the weighted average of all grids where the weight is proportional to the grid area in the region. We then aggregate data by season as follows: (i) Winter, from December to February; (ii) Spring, from March to May; (iii) Summer, from June to August; and (iv) Fall, from September to November.

Three weather variables are considered: temperature, temperature deviation (daily spread between maximum and minimum temperature), and precipitation. Four climate scenarios are used: the RCPs 2.6, 4.5, 6.0, and 8.5. The first three, *i.e.*, the RCPs 2.6, 4.5 and 6.0 are characterized by increasing greenhouse gas concentrations with a peak around 2020, 2040, and 2060, respectively, followed by a slow decline. The last scenario, the RCP 8.5, is less optimistic in terms of emissions and leads to a rapidly increasing concentration over the whole century.

In addition to historical values, ranging from 1991 to 2009, two time horizon are highlighted: a short one, ranging from 2009 to 2050, and a long one, ranging from 2051 to to end of the 21st century.

2.2 Descriptive Statistics

The analysis of wheat and corn yield is made on sub-samples of data, considering northern and southern European regions separately. Descriptive statistics of weather variables used in these sub-samples are reported in Table B.1.

Table B.1: Descriptive Statistics of Climate Variables

Data for Wheat Yield Model

		Historical		RCP 2.6				RCP 4.5				RCP 6.0				RCP 8.5			
				Short-run		Long-run		Short-run		Long-run		Short-run		Long-run		Short-run		Long-run	
Variable	Unit	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Temp. (winter)	^oC	4.62	3.06	4.63	3.19	5.2	3.04	4.86	3.09	5.41	2.99	4.71	3.26	5.74	2.94	4.83	3.22	6.54	2.91
Temp. (spring)	^oC	9.15	2.64	9.08	2.58	9.61	2.51	9.64	2.56	9.93	2.57	9.37	2.59	10.13	2.63	9.62	2.68	10.93	2.68
Temp. (summer)	^oC	17.6	2.2	17.77	2.34	18.14	2.36	17.96	2.35	18.65	2.53	17.8	2.4	18.81	2.58	18.14	2.43	19.81	2.71
Temp. (fall)	^oC	10.39	2.79	10.76	2.69	11.31	2.69	10.97	2.7	11.77	2.71	10.9	2.75	11.95	2.63	10.89	2.73	13.05	2.76
Temp. Dev. (winter)	^oC	4.49	0.98	4.37	1	4.38	0.96	4.32	0.96	4.32	0.98	4.45	1.04	4.32	1	4.4	1.04	4.31	0.98
Temp. Dev. (spring)	^oC	7.09	1.36	6.98	1.4	7.01	1.34	7	1.37	7.05	1.43	7.08	1.43	7.07	1.44	7.13	1.44	7.07	1.47
Temp. Dev. (summer)	^oC	7.77	1.52	7.63	1.55	7.6	1.53	7.62	1.52	7.66	1.62	7.66	1.57	7.71	1.69	7.67	1.58	7.62	1.69
Temp. Dev. (fall)	^oC	5.32	1.21	5.2	1.2	5.26	1.18	5.22	1.16	5.21	1.23	5.28	1.21	5.26	1.27	5.24	1.27	5.24	1.27
Precip. (winter)	m	8.1	3.16	7.78	2.63	8.26	2.84	8.13	2.95	8.32	2.84	8.29	2.99	8.31	2.96	8.15	2.95	8.71	3.12
Precip. (spring)	m	6.68	1.99	6.67	2.13	6.68	2.17	6.6	2.06	6.49	2.11	6.44	2.16	6.29	2.11	6.28	2.1	6.65	2.45
Precip. (summer)	m	6.35	2.72	6.3	2.63	6.44	2.7	6.27	2.6	6.04	2.68	6.16	2.58	5.95	2.74	6.31	2.65	6.09	2.8
Precip. (fall)	m	8.75	2.79	8.89	2.44	8.6	2.47	8.47	2.5	9.01	2.51	8.58	2.55	8.55	2.59	8.7	2.6	8.56	2.64

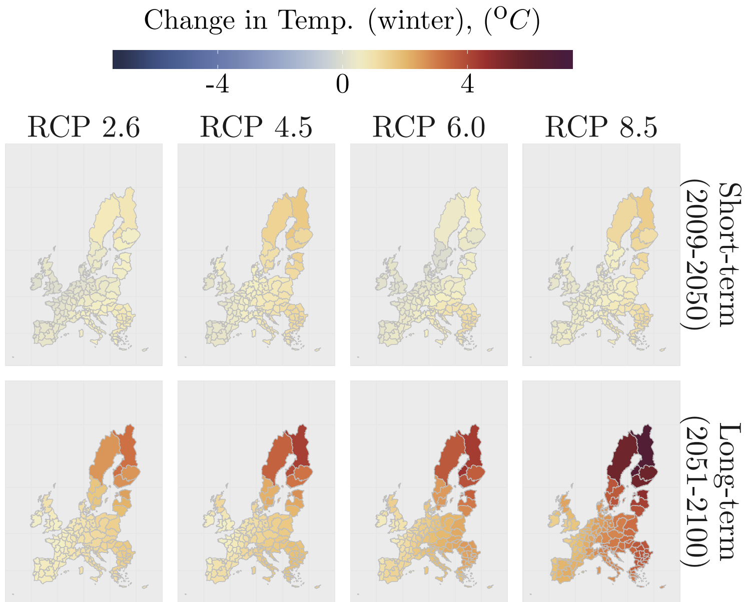
Data for Corn Yield Model

		Historical		RCP 2.6				RCP 4.5				RCP 6.0				RCP 8.5			
				Short-run		Long-run		Short-run		Long-run		Short-run		Long-run		Short-run		Long-run	
Variable	Unit	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Temp. (winter)	^oC	5.1	2.53	5.26	2.44	5.76	2.43	5.44	2.45	5.95	2.41	5.37	2.43	6.3	2.33	5.45	2.49	7.08	2.37
Temp. (spring)	^oC	9.72	1.95	9.7	1.82	10.22	1.81	10.28	1.8	10.56	1.85	10	1.83	10.75	1.94	10.26	1.94	11.55	2
Temp. (summer)	^oC	18.13	1.6	18.31	1.76	18.72	1.75	18.55	1.74	19.26	1.89	18.38	1.8	19.4	1.97	18.74	1.78	20.41	2.14
Temp. (fall)	^oC	10.87	2.35	11.29	2.16	11.83	2.2	11.49	2.18	12.31	2.18	11.45	2.22	12.44	2.17	11.4	2.24	13.57	2.3
Temp. Dev. (winter)	^oC	4.62	0.91	4.49	0.93	4.51	0.89	4.43	0.9	4.48	0.91	4.54	0.96	4.47	0.93	4.53	0.97	4.49	0.9
Temp. Dev. (spring)	^oC	7.34	1.21	7.2	1.29	7.24	1.23	7.22	1.25	7.31	1.31	7.32	1.31	7.33	1.32	7.37	1.32	7.35	1.35
Temp. Dev. (summer)	^oC	8.13	1.34	7.97	1.39	7.93	1.38	7.96	1.35	8.01	1.44	8	1.42	8.07	1.51	8.01	1.42	7.98	1.51
Temp. Dev. (fall)	^oC	5.59	1.08	5.46	1.09	5.53	1.07	5.48	1.05	5.5	1.1	5.56	1.09	5.56	1.15	5.52	1.15	5.54	1.15
Precip. (winter)	m	8.26	3.33	8.07	2.97	8.59	3.24	8.4	3.33	8.68	3.27	8.55	3.29	8.62	3.43	8.44	3.24	9.11	3.61
Precip. (spring)	m	6.98	2.01	6.95	2.2	7.01	2.31	6.88	2.1	6.71	2.16	6.67	2.23	6.51	2.16	6.44	2.16	6.88	2.55
Precip. (summer)	m	6.49	2.67	6.45	2.63	6.56	2.71	6.41	2.61	6.07	2.68	6.26	2.61	6.01	2.8	6.46	2.66	6.08	2.82
Precip. (fall)	m	9.2	3.02	9.37	2.62	9.03	2.72	8.95	2.83	9.44	2.75	8.95	2.7	8.87	2.81	9.09	2.85	8.87	2.75

Notes: For each weather variable, average and standard error are given for the historical period (1992–2009), for projections in the short-run (2009–2050), and in the long-run (2051–2100). Four scenarios are considered: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. Descriptive statistics are given for the sample used for wheat yield model (top) and for corn yield (bottom).

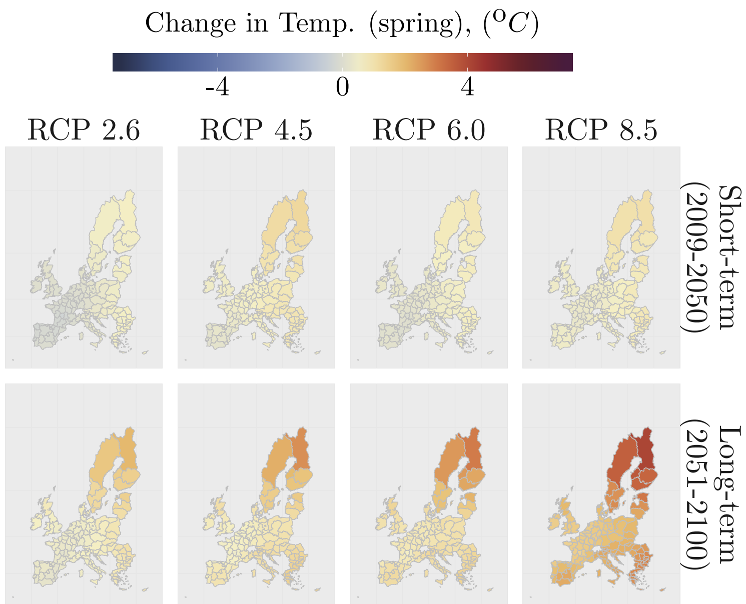
2.3 Projected Weather Variables

Using the historical period (1991–2009) as a benchmark, we compute the average regional and seasonal change in the short-run (2009–2050) and in the long-run (2051–2100) for the three weather variables used in the analysis, under each of the four climate scenarios. Figures B.1 to B.4 display the average change in temperature, in degree Celsius. Finally, figures B.5 to B.8 show the average percentage change in precipitation.



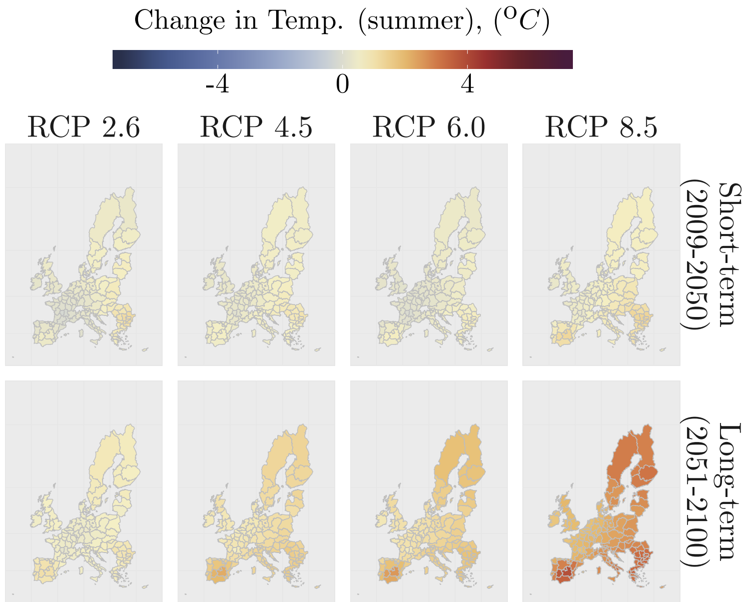
Note: Each map shows the change in temperature in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.1: Projected Changes in Winter Temperature



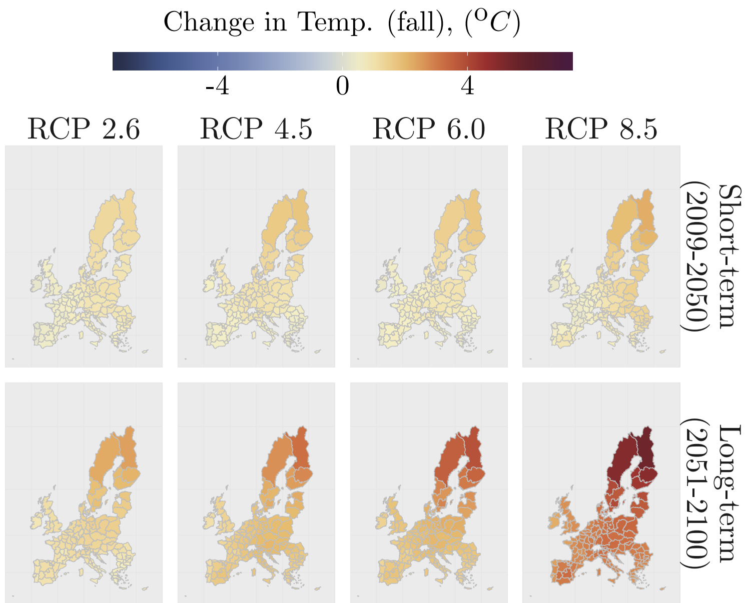
Note: Each map shows the change in temperature in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.2: Projected Changes in Spring Temperature



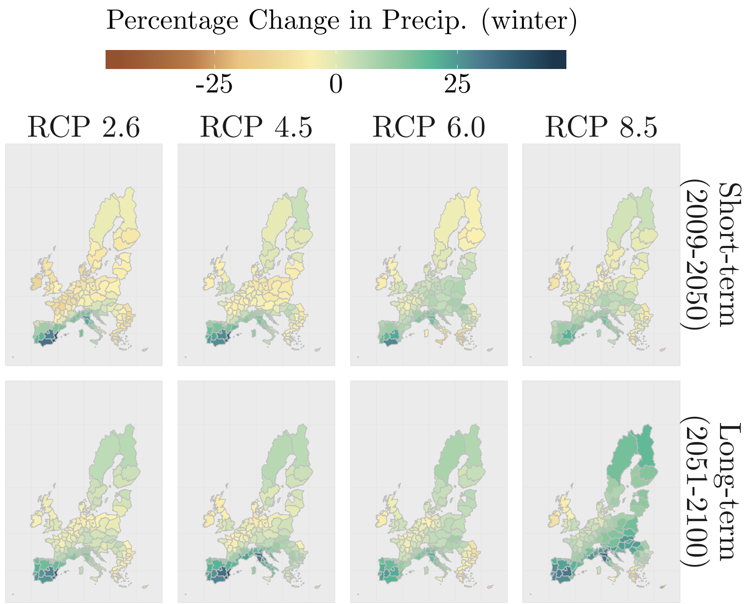
Note: Each map shows the change in temperature in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.3: Projected Changes in Summer Temperature



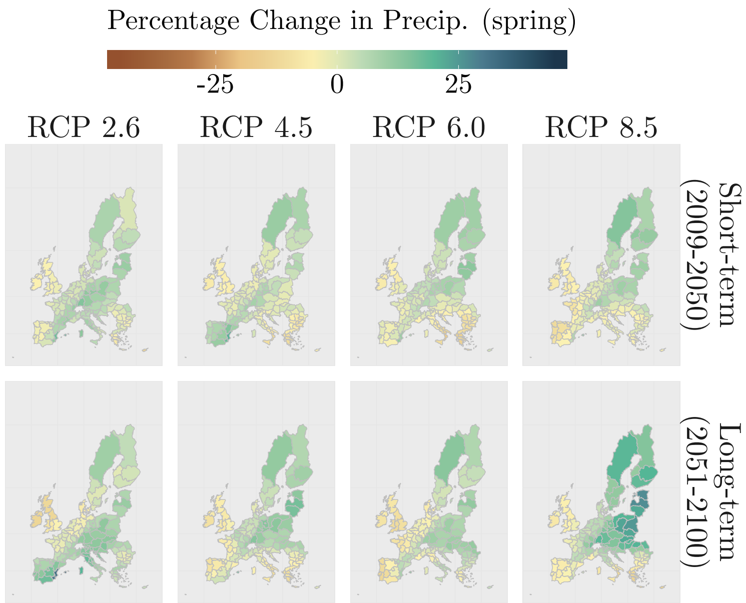
Note: Each map shows the change in temperature in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.4: Projected Changes in Fall Temperature



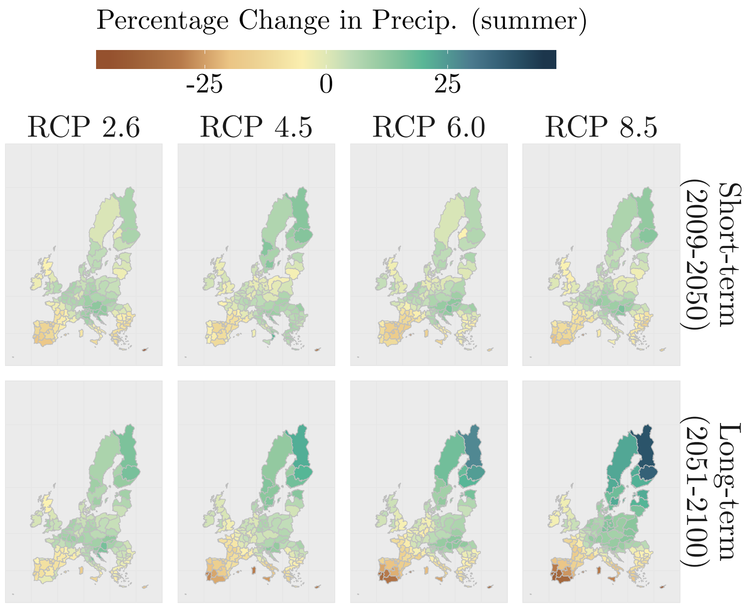
Note: Each map shows the percentage change in precipitation in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.5: Projected Percentage Changes in Winter Precipitation



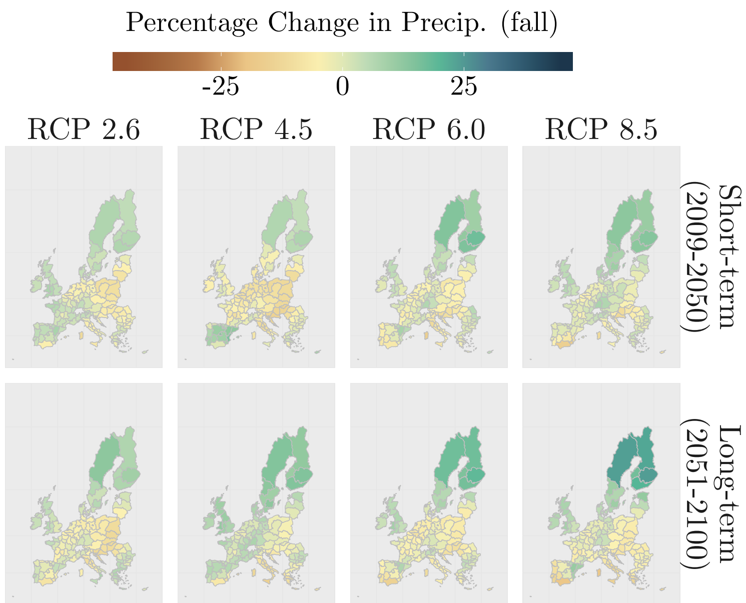
Note: Each map shows the percentage change in precipitation in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.6: Projected Percentage Changes in Spring Precipitation



Note: Each map shows the percentage change in precipitation in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.7: Projected Percentage Changes in Summer Precipitation



Note: Each map shows the percentage change in precipitation in the short-run (2009-2050) (top panels) and in the long-run (2051-2100) (bottom panels) compared to the average historical value (1991-2009), under each scenario (RCPs 2.6, 4.5, 6.0, and 8.5).

FIGURE B.8: Projected Percentage Changes in Fall Precipitation

Appendix C

Climate Change and Business Cycles: Technical Appendix

1 Data

Agricultural production price inflation data begins in 1994:Q2. We backcast the missing data by fitting an $ARMA(1,1)$ model with CPI inflation and soil moisture deficit index as external regressors.

Climate data are obtained from weather stations at a monthly rate. The measure we use is based on soil moisture deficit observations.

- **Gross domestic product**: real per capita output, expenditure approach, seasonally adjusted. *Source:* Statistics New Zealand.
- **CPI inflation**: all groups index, *Source:* Statistics New Zealand.
- **Agricultural output**: real agriculture, fishing and forestry gross domestic product, seasonally adjusted. *Source:* Statistics New Zealand.
- **Agricultural producer price inflation**: agriculture, fishing and forestry producer price index. *Source:* Statistics New Zealand.
- **Population**: actual population of working age, in thousands, seasonally adjusted. *Source:* Statistics New Zealand.
- **Interest rate**: 3-Month rates and yields: bank bills for New Zealand, not seasonally adjusted. *Source:* Main Economic Indicators, OECD.

- **Real exchange rate**: real trade weighted index. *Source:* Reserve Bank of New Zealand.
- **Climate**: soil moisture deficit at the station level. *Source:* National Climate Database, National Institute of Water and Atmospheric Research.

2 Model Description

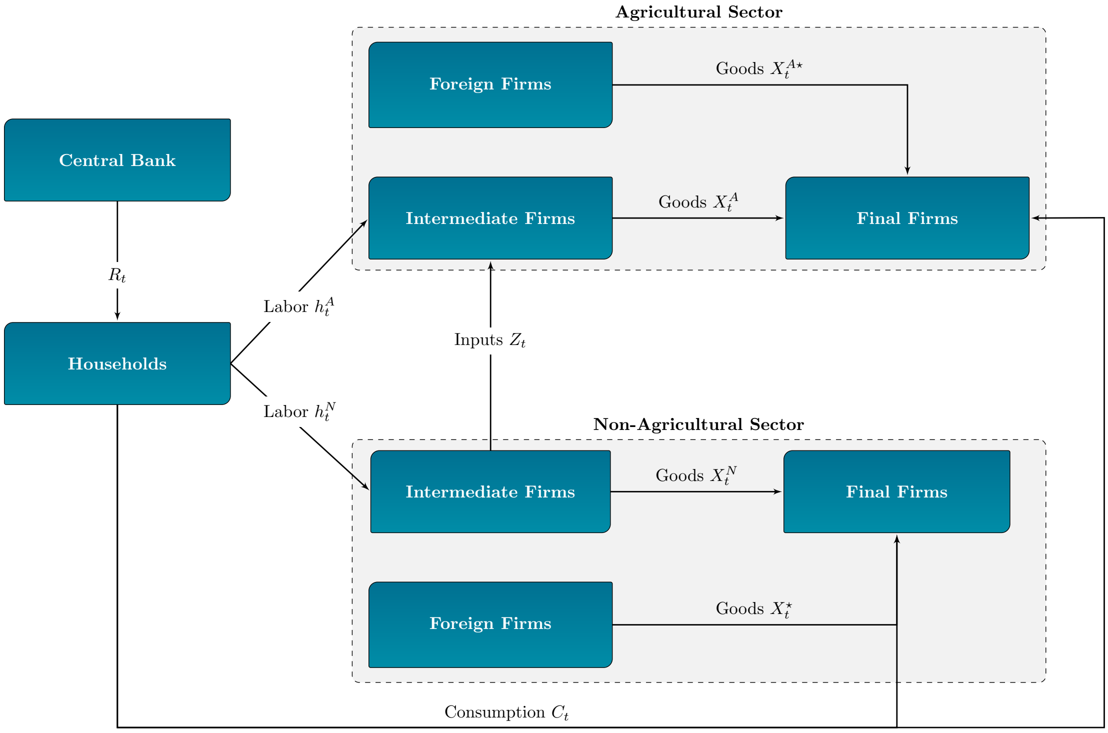


Figure C.1: A Small Open Economy Featuring Two Sectors: Agricultural and Non-agricultural Sectors

As shown in fig. C.1, the domestic economy is populated by:

- Households that consume save and supply labour;
- Intermediate and final firms operating in two sectors: the agricultural sector and the non-agricultural one. In both of them:
  - intermediate firms supply differentiated goods in a monopolistically competitive market and set prices in a staggered basis,
  - final producers aggregate the differentiated goods from both domestic and foreign intermediate firms and sell it to households. The agricultural final firm uses intermediate goods from firms of both sectors;

- A Central bank that decides the interest rate according to a Taylor rule.

3 A Sketch of the Model

This section is devoted to a formal presentation of the DSGE model. Our model is two-sector two-good economy in a small open economy setup with standard New Keynesian nominal frictions and a flexible exchange rate regime. Small open economy models usually include two countries. The home country participates in international trade, but is too small compared to its trading partners to cause aggregate fluctuation to world output, price and interest rate. The foreign country, gathering most of the trading partners of the home country, is thus not affected by macroeconomic shocks from the home country but its own macroeconomic developments affect the home country through the trade balance and the exchange rate.

The home economy, *i.e.*, New Zealand, is populated by households, final firms, agricultural and non-agricultural intermediate firms and a central bank. Intermediate producers in each sector enjoy market power to maximize their profits and produce differentiated goods. Final goods producers use a packing technology to aggregate both home and foreign intermediate goods to produce a homogeneous good sold to households. The final product is a composite of domestically produced and imported goods, thus creating a trading channel adjusted by the real exchange rate. Nominal rigidities in the agricultural and non-agricultural sectors generate inflation dynamics that are damped by the central bank though the adoption of an inflation targeting regime.

The foreign economy is modelled through six structural and linear equations that aim at capturing the key patterns of business cycles of New Zealand's trading partners. The description of these equations are left in appendix 3.4.

3.1 Households

There is a continuum of identical households who consume, save and work in intermediate firms. The total number of households is normalized to 1. The representative household $j \in [0, 1]$ maximizes the welfare index expressed as the expected sum of utilities discounted by $\beta \in (0,1)$:

$$\mathcal{W}_{jt} = \mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{\left(C_{jt+\tau} - hC_{t-1+\tau}\right)^{1-\sigma_C}}{1-\sigma_C} \exp\left(\frac{\sigma_C - 1}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right) \right] \right\}, \tag{C.1}$$

where variable C_{jt} is the consumption index, $h \in [0,1]$ is a parameter that accounts for external consumption habits, h_{jt} is a labour effort index for the agricultural and non-agricultural sectors, and σ_C and σ_H represent consumption aversion and labour disutility, respectively. Following the seminal contribution of Smets and Wouters (2007), households preferences are assumed to be non-separable in consumption, so an increase in hours worked has a positive effect on the marginal utility of consumption.[1]

The representative household allocates total consumption C_{jt} between two types of consumption goods produced by the non-agricultural and agricultural sectors denoted C_{jt}^N and C_{jt}^A respectively. The CES consumption bundle is determined by:

$$C_{jt} = \left((1-\varphi)^{\frac{1}{\mu}} \left(C_{jt}^N\right)^{\frac{\mu-1}{\mu}} + (\varphi)^{\frac{1}{\mu}} \left(C_{jt}^A\right)^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}, \tag{C.2}$$

where $\mu \geq 0$ denotes the substitution elasticity between the two types of consumption goods, and $\varphi \in [0,1]$ is the fraction of agricultural goods in the household's total consumption basket. The corresponding consumption price index thus reads as follows:

$$P_t^C = \left[(1-\varphi) \left(P_{y,t}^N\right)^{1-\mu} + \varphi \left(P_{y,t}^A\right)^{1-\mu} \right]^{\frac{1}{1-\mu}}, \tag{C.3}$$

where $P_{y,t}^N$ and $P_{y,t}^A$ are the final prices of non-agricultural and agricultural goods respectively. Demand for each type of final good is a fraction of the total consumption index adjusted by its relative price:

$$C_{jt}^N = (1-\varphi) \left(P_{y,t}^N / P_t^C\right)^{-\mu} C_{jt} \text{ and } C_{jt}^A = \varphi \left(P_{y,t}^A / P_t^C\right)^{-\mu} C_{jt}. \tag{C.4}$$

Following Iacoviello and Neri (2010), we introduce imperfect substitutability of labour supply between the durable and non-durable sector to explain co-movements at the sector level by defining a CES labour disutility index:

$$h_{jt} = \left[n \left(h_{jt}^N\right)^{1+\iota} + (1-n) \left(h_{jt}^A\right)^{1+\iota} \right]^{1/(1+\iota)} \tag{C.5}$$

[1] We refer the reader to Greenwood et al. (1988) for a discussion of the implications of non-separable preferences on business cycles.

The labour disutility index consists of hours worked in the non-agricultural sector h_{jt}^N and agriculture sector h_{jt}^A, with n denoting the relative share of employment in the non-agricultural sector. Reallocating labour across sectors is costly and is governed by the substitutability parameter $\iota \geq 0$.[2]

Expressed in real terms and dividing by the consumption price index P_t^C, the budget constraint for the representative household can be represented as:

$$\sum_{s=N,A} \chi_S w_t^s h_{jt}^s + \frac{\Pi_{jt}}{P_t^C} + \frac{R_{t-1}}{\pi_t^C} b_{jt-1} + \frac{R_{t-1}^*}{\pi_t^C} b_{jt-1}^* = C_{jt} + b_{jt} + e_t b_{jt}^* + \frac{P_{y,t}^N}{P_t^C} e_t \Phi_B(b_{jt}^*). \tag{C.6}$$

The income of the representative household is made up of labour income with a real wage w_t^s in each sector,[3] profits Π_{jt} generated by imperfect competition in goods, and real riskless domestics bonds b_{jt} and foreign bonds b_{jt}^*. Domestic and foreign bonds are remunerated at a domestic R_{t-1} and a foreign R_{t-1}^*, respectively, nominal gross interest rates decided by central banks of each country and adjusted by the domestic inflation rate $\pi_t^C = P_t^C / P_{t-1}^C$. Household's foreign bonds purchases are affected by the nominal exchange rate e_t (an increase in e_t can be interpreted as an appreciation of the domestic exchange rate). The household's expenditure side includes its consumption basket C_{jt}, bonds and risk-premium cost $\Phi(b_{jt}^*)$=$0.5\chi_B(b_{jt}^*)^2$ paid in terms of domestic final goods at a market price $P_{y,t}^N$.[4] Parameter $\chi_B > 0$ denotes the magnitude of the cost paid by domestic households when purchasing foreign bonds.

[2]If ι equals zero, hours worked across the two sectors are perfect substitutes, leading to a negative correlation between the sectors that is not consistent with the data. Positive values of ι capture some degree of sector specificity and imply that relative hours respond less to sectoral wage differentials.

[3]Real labour income is affected by $\chi_s > 0$, a sector-specific shift parameter that allows us to calibrate the steady state of hours worked in each sector. This is a common assumption in real business cycle models.

[4]This cost function aims at removing a unit root component that emerges in open economy models without affecting the steady state of the model. See Schmitt-Grohé and Uribe (2003) for a discussion of closing open economy models.

The dynamic Lagrangian reads as follows:

$$
\begin{aligned}
\mathcal{L}_t = \mathbb{E}_t\{\sum_{\tau=0}^{\infty}\beta^{\tau}[&\frac{\left(C_{jt+\tau} - hC_{t-1+\tau}\right)^{1-\sigma_C}}{1-\sigma_C}\exp\left(\frac{\sigma_C - 1}{1+\sigma_H}h_{jt+\tau}^{1+\sigma_H}\right) \\
&+ \lambda_{t+\tau}^{c}\left[\sum_{s=N,A}\chi_S w_{t+\tau}^{s} h_{jt+\tau}^{s} + \frac{\Pi_{jt+\tau}}{P_{t+\tau}^{C}} + \frac{R_{t-1+\tau}}{\pi_{t+\tau}^{C}} b_{jt-1+\tau} + \frac{R_{t-1+\tau}^{*}}{\pi_{t+\tau}^{C}} b_{jt-1+\tau}^{*}\right] \\
&- \lambda_{t+\tau}^{c}\left[C_{jt+\tau} + b_{jt+\tau} + e_{t+\tau} b_{jt+\tau}^{*} + \frac{P_{y,t+\tau}^{N}}{P_{t+\tau}^{C}} e_t \Phi_B(b_{jt+\tau}^{*})\right] \\
&+ \lambda_{t+\tau}^{h}\left[n\left(h_{jt+\tau}^{N}\right)^{1+\iota} + (1-n)\left(h_{jt+\tau}^{A}\right)^{1+\iota} - h_{jt+\tau}^{1+\iota}\right]]\}
\end{aligned}
$$

where λ_t^c and λ_t^h are Lagrange multipliers associated to each constraint and can be interpreted as the marginal utility of consumption and marginal disutility of labour supply, respectively. Constraints are included in the discounted sum as they bind every periods.

First-order conditions are:

$$
\begin{aligned}
C_{jt} &: \left(C_{jt+\tau} - hC_{t-1+\tau}\right)^{-\sigma_C}\exp\left(\frac{\sigma_C - 1}{1+\sigma_H}h_{jt}^{1+\sigma_H}\right) - \lambda_t^c = 0 \\
h_{jt} &: (\sigma_C - 1)h_{jt}^{\sigma_H}\mathcal{U}_{jt} - \lambda_t^h\frac{h_{jt}^{\iota}}{1+\iota} = 0 \\
h_{jt}^N &: \lambda_t^c \chi_N w_t^N + \lambda_t^h \frac{n\left(h_{jt}^N\right)^{\iota}}{1+\iota} = 0 \\
h_{jt}^A &: \lambda_t^c \chi_A w_t^A + \lambda_t^h \frac{(1-n)\left(h_{jt}^A\right)^{\iota}}{1+\iota} = 0 \\
b_{jt} &: -\lambda_t^c + \beta\lambda_t^c\frac{R_t}{\pi_{t+1}^C} = 0 \\
b_{jt}^* &: -\lambda_t^c e_t\left(1 + \frac{P_{y,t}^N}{P_t^C}\chi_B b_{jt}^*\right) + \beta\lambda_{t+1}^c\frac{R_t^*}{\pi_{t+1}^C}
\end{aligned}
$$

The first-order conditions solving the household's optimization problem are obtained by maximizing welfare index in eq. (C.1) under the budget constraint in eq. (C.6) given the labour sectoral re-allocation cost in eq. (4.3). First, the marginal utility of consumption is determined by:[5]

$$
\lambda_t^c = \exp\left(\frac{\sigma_C - 1}{1+\sigma_H}h_{jt}^{1+\sigma_H}\right)\left(C_{jt} - hC_{t-1}\right)^{-\sigma_C}. \tag{C.7}
$$

[5]In equilibrium, the marginal utility of consumption equals the Lagrange multiplier λ_t^c associated with the household budget constraint.

The first-order condition determines the household labour supply in each sector:

$$w_t^N = h_{jt}^{\sigma_H} \frac{n}{\chi_N} \left(\frac{h_{jt}^N}{h_{jt}} \right)^{\iota} (C_{jt} - hC_{t-1}), \tag{C.8}$$

$$w_t^A = h_{jt}^{\sigma_H} \frac{(1-n)}{\chi_A} \left(\frac{h_{jt}^A}{h_{jt}} \right)^{\iota} (C_{jt} - hC_{t-1}), \tag{C.9}$$

where w_t^N and w_t^A are the real wages in the non-agricultural sector and the agricultural sector, respectively.

The Euler condition on domestic bonds that determines the optimal consumption path is:

$$\beta \mathbb{E}_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} \frac{1}{\mathbb{E}_t \left\{ \pi_{t+1}^C \right\}} \right\} = \frac{1}{R_t}. \tag{C.10}$$

Finally, the Euler condition on foreign bonds, after substituting the Lagrange multiplier, can be expressed as the real exchange rate determination under incomplete markets:

$$\mathbb{E}_t \left\{ \frac{e_{t+1}}{e_t} \right\} = \left(1 + \chi_B p_{y,t}^N b_{jt}^*\right) \frac{R_t}{R_t^*}, \tag{C.11}$$

where $p_{y,t}^N = P_{y,t}^N / P_t^C$ denotes the relative price of final goods with respect to the consumption price index.

We define the real exchange rate as the ratio of final goods prices, expressed in a common currency:

$$rer_t = e_t \frac{P_t^{C*}}{P_t^C}, \tag{C.12}$$

where P_t^{C*} denotes the foreign price.

3.2 Production

The firm block is populated by two groups of agents: intermediate goods firms and final goods firms. Intermediate goods firms produce differentiated goods $i \in [0,1]$, decide on labour on a perfectly competitive inputs market, and set prices according to a Rotemberg (1982) technology. Final goods producers act as goods bundlers by combining national and foreign intermediate goods to produce a homogeneous non-tradable final good that will be sold to domestic households.

Intermediate firms are divided in two sectors $s = \{N, A\}$, where the non-agricultural N and agricultural sectors A are of size n and $1-n$, respectively. Firms operating in the non-agricultural sector are standard with real business cycle models, they combine hours worked and total factor productivity (TFP) to produce a differentiated type of goods. In addition, firms operating in the agricultural sectors combine labour, TFP, intermediate goods as well as land to produce differentiate types of agricultural goods. With this technology, an adverse weather shock on farm business triggers a lower demand for final goods which in turn depresses output. Assuming $n = 1$ and the model boils down to a very standard (one sector) small open economy New-Keynesian model such as Galí and Monacelli (2005).

3.2.1 Final Firms

In each sector $s = \{N, A\}$, where N and A denote non-agricultural and agricultural sectors, respectively, we assume that the production of the final good is performed as in Rabanal and Tuesta (2010). A continuum of final firms purchases a composite of intermediate home goods X_t^s, and a composite of intermediate foreign-produced goods X_t^{s*} to produce a differentiated final good product Y_t^s using the following CES technology:

$$Y_t^s = \left((1-\alpha_s)^{1/\mu_s} \left(X_t^s\right)^{(\mu_s-1)/\mu_s} + \alpha_s^{1/\mu_s} \left(X_t^{s*}\right)^{(\mu_s-1)/\mu_s} \right)^{\mu_s/(\mu_s-1)}, \text{for } s = \{N, A\}, \tag{C.13}$$

where α_s denotes the share of foreign-produced goods that are used for the production of the final good, and μ_s is the elasticity of substitution between domestically produced and imported intermediate goods in both countries. A value of $\alpha_s = 0$ implies the autarky of this market, while $\alpha_s < 0.5$ reflects a home bias in the preferences of firms.

The composite intermediate goods for the non-agricultural sector bought at home and abroad are:

$$X_t^N = \left(\int_0^n \left(X_{it}^N\right)^{(\epsilon_N-1)/\epsilon_N} \mathrm{d}i \right)^{\epsilon_N/(\epsilon_N-1)} \text{ and } X_t^{N*} = \left(\int_0^n \left(X_{it}^{N*}\right)^{(\epsilon_N-1)/\epsilon_N} \mathrm{d}i \right)^{\epsilon_N/(\epsilon_N-1)}, \tag{C.14}$$

while for the agricultural sector:

$$X_t^A = \left(\int_n^1 \left(X_{it}^A\right)^{(\epsilon_A-1)/\epsilon_A} \mathrm{d}i \right)^{\epsilon_A/(\epsilon_A-1)} \text{ and } X_t^{A*} = \left(\int_n^1 \left(X_{it}^{A*}\right)^{(\epsilon_A-1)/\epsilon_A} \mathrm{d}i \right)^{\epsilon_A/(\epsilon_A-1)} \tag{C.15}$$

where ϵ_s for $s = \{A, N\}$ is the elasticity of substitution between the types of intermediate goods in each sector.

We consider a two-stage problem for final firms. In the first stage, they decide the amount of imports and domestic intermediate goods by maximizing profits under the CES technology constraint in eq. (C.13):

$$\max_{\{Y_t^s, X_t^s, X_t^{s*}\}} P_{y,t}^s Y_t^s - P_t^s X_t^s - P_t^{s*} X_t^{s*}. \tag{C.16}$$

where $P_{y,t}^s$ denotes the price of final goods Y_t^s produced in sector s, while X_t^s and X_t^{s*} are intermediate inputs involved in the production process of final goods.

In the second stage of the problem, final goods producers decide the optimal amount of varieties produced by intermediates firms in each sector using their packing technologies in eq. (C.14) and eq. (C.15). For domestically produced goods, the problem reads as follows:[6]

$$\max_{\{X_t^N, X_{it}^N\}} P_t^N X_t^N - \int_0^n P_{it}^N X_{it}^N \mathrm{d}i \text{ and } \max_{\{X_t^A, X_{it}^A\}} P_t^A X_t^A - \int_n^1 P_{it}^A X_{it}^A \mathrm{d}i. \tag{C.17}$$

After solving the two-stage problem in each sector, the following first-order conditions emerge for both sectors:

$$X_{it}^s = (1-\alpha_s)\left(\frac{P_t^s}{P_{y,t}^s}\right)^{-\mu_s}\left(\frac{P_{it}^s}{P_t^s}\right)^{-\epsilon_s} Y_t^s, \tag{C.18}$$

$$X_{it}^{s*} = \alpha_s\left(e_t\frac{P_t^{s*}}{P_{y,t}^s}\right)^{-\mu_s}\left(\frac{P_{it}^{s*}}{P_t^{s*}}\right)^{-\epsilon_s} Y_t^s, \text{ for } s = \{N, A\} \tag{C.19}$$

Finally concerning price indexes. The price index for final goods reads as follows:

$$P_{y,t}^s = \left((1-\alpha_s)\left(P_t^s\right)^{1-\mu_s} + \alpha_s\left(e_t P_t^{s*}\right)^{1-\mu_s}\right)^{1/(1-\mu_s)}, \text{ for } s = \{N, A\}, \tag{C.20}$$

while the zero-profit assumption for intermediate goods varieties packing activity delivers the following price index for each sectors $P_t^N = [\frac{1}{n}\int_0^n P_{it}^{N\,1-\epsilon_N}\,\mathrm{d}i]^{1/(1-\epsilon_N)}$ and $P_t^A = [\frac{1}{1-n}\int_n^1 P_{it}^{A\,1-\epsilon_A}\,\mathrm{d}i]^{1/(1-\epsilon_A)}$.

[6]The same result is symmetrically obtained for foreign goods which are not developed here for clarity purposes.

3.2.2 Agricultural Production and Weather Variability

To investigate the implications of weather variations as a source of aggregate fluctuation, we introduce into the model a weather variable, denoted ε_t^W, that captures variations in soil moisture affecting the production process of farmers. The measure we use is based on soil moisture deficit observations calculated from the daily water balance.[7] A positive realization of ε_t^W depicts a prolonged episode of dryness that damages agricultural output and generates inflation pressures. We assume that the aggregate drought index follows a stochastic exogenous process driven by two shocks:

$$\varepsilon_t^W = (1-\rho_W) + \rho_W \varepsilon_{t-1}^W + \eta_t^W + \tilde{\eta}_{t-1}^W, \qquad \rho_W \in [0,1) \tag{C.21}$$

The first shock, denoted η_t^W, is a traditional shock to the real business cycle that impacts the level of soil moisture in the same period in which farmers see it. The second, $\tilde{\eta}_{t-1}^W$, is a news shock and is differentiated from the former in that farmers observe a weather news shock in advance (here, one quarter).[8] Thus, this shock allows us to evaluate whether farmers are anticipating drought events one quarter in advance by capturing macroeconomic fluctuations one quarter before the realization of the weather shock.[9]

To bridge weather variations with business cycle fluctuations, we define a damage variable d_t determining how variable weather conditions $\log(\varepsilon_t^W)$ may induce inertial aggregate fluctuations:

$$d_t = \rho_d d_{t-1} + \log(\varepsilon_t^W), \qquad \rho_d \in [0,1) \tag{C.22}$$

where ρ_d captures some persistence of damage after an adverse drought event shock. Here, it is important to disentangle parameters ρ_W from eq. (C.21) and ρ_d from eq. (C.22): the autoregressive component ρ_W captures the estimated persistence of a drought

[7] The soil moisture variable measures the net impact of rainfall entering the pasture root zone in the soil which is then lost from this zone as a result of evapotranspiration or use of water by plants.

[8] We follow the news-driven business cycle literature, as exemplified by Beaudry and Portier (2006), Barsky and Sims (2011), and Schmitt-Grohé and Uribe (2012), to introduce climate-news shocks as a source of macroeconomic fluctuation.

[9] Anticipating the results from the estimation exercise, we have evaluated the ability of farmers to expect weather shocks more than one quarter in advance ; however we find evidence that farmers are not able to predict drought events and that they are rather surprised by weather shocks.

shock, while ρ_d catches the persistence of its damages. The main underlying motivation is that damages to the economy might be more persistent than the weather shock itself, as showed by the VAR models.[10]

The production component of agriculture is strongly inspired by Restuccia et al. (2008) to the extent that agricultural output is Cobb-Douglas in land, intermediate inputs, and labour inputs.[11] In addition to this modeling choice, we introduce a damage function $\Gamma_X(\cdot)$ in the spirit of Integrated Assessment Models, which connects weather to agricultural output.

Each representative firm $i \in [n, 1]$ operating in the agricultural sector has the following production function:

$$X_{it}^{A} = \varepsilon_t^Z Z_{it}^{\omega} \left(\left(\Gamma_X \left(d_t, d_{t-1} \right) \bar{L}_i \right)^{1-\sigma} \left(\kappa_i H_{it}^{A} \right)^{\sigma} \right)^{1-\omega}, \tag{C.23}$$

where X_{it}^A is the production function of the intermediate agricultural good that combines a (fixed) land endowment $\bar{L}_i$ for each farmer i, labour demand H_{it}^A and non-agricultural inputs Z_{it}. Production is subject to an economy-wide technology shock ε_t^Z.[12] The parameter $\omega \in [0, 1]$ is the elasticity of output to intermediate inputs, $\sigma \in [0, 1]$ denotes the share of production/land in the production process of agricultural goods, and $\kappa_i > 0$ is a technology parameter endogenously determined in the steady state. The economy-wide technology shock ε_t^Z affects both sectors agricultural and non-agricultural sectors by capturing fluctuations associated with declining hours worked and prices coupled with increasing output.

Agricultural production is tied up with exogenous weather conditions through a damage function $\Gamma_X(\cdot)$ that alters land productivity. This function has a simple form with one lag aiming at capturing the hump-shaped response of output to weather shock:

$$\Gamma_X \left(d_t, d_{t-1} \right) = 1 + \gamma_0^X d_t + \gamma_1^X d_{t-1}, \tag{C.24}$$

where $\gamma_0^X, \gamma_1^X \in (-\infty, +\infty)$ are elasticities that are estimated agnostically (*i.e.*, without tight priors) during the estimation exercise. In our setup, we are interested in the

[10]We refer to Buckle et al. (2007) and Kamber et al. (2013) for VAR models highlighting the hysteresis effects of weather shocks on business cycles.

[11]We refer to Mundlak (2001) for discussions of related conceptual issues and empirical applications regarding the functional forms of agricultural production. In an alternative version of our model based on a CES agricultural production function, the fit of the DSGE model is not improved, and the identification of the CES parameter is weak.

[12]Technology is characterized as an $AR(1)$ shock process: $\varepsilon_t^Z = 1 - \rho_Z + \rho_Z \varepsilon_{t-1}^Z + \eta_t^Z$ with $\eta_t^Z \sim \mathcal{N}(0, \sigma_Z)$, where $\rho_A \in [0, 1)$ denotes the $AR(1)$ term in the technological shock process.

short-run implications of weather shocks, leaving aside the neutral long run effects with $\Gamma_X\left(\bar{d},\bar{d}\right)=1$, where $\bar{d}$ denotes the (zero) deterministic steady state of damages induced by drought events. The parameter γ_1^X captures the lagged response of output after drought events, the introduction of this parameter is empirically motivated by the time prices usually take to adjust to climate shocks, as assumed by Bloor and Matheson (2010).

In addition to this damage function for output, inputs costs are affected by a similar function. The real costs paid by farmers read as follows:

$$w_t^A H_{it}^A + p_t^N Z_{it} \Gamma_X\left(d_t, d_{t-1}\right), \tag{C.25}$$

where w_t^A is the real wage offered to households hired in the agricultural sector, and $p_t^N = P_t^N/P_t^C$ denotes the relative price of intermediate goods, with P_t^C as the consumer price index. The demand for intermediate goods Z_{it} is affected by $\Gamma_X\left(d_t, d_{t-1}\right)$ which aims at capturing extra-consumption of intermediate goods following a drought event. A drought shock increases the feed budget, as dairy cattle requires more water as temperature, humidity and production levels rise. Farming activities also demand more water to offset soil dryness by increasing field irrigation. This damage function captures the demand effects in the intermediate sector, and the shape of this damage function reads as in eq. (C.24) with different elasticities denoted γ_0^Z and $\gamma_1^Z \in (-\infty, +\infty)$.

To introduce nominal rigidities, we assume that firms must solve a two-stage problem. In the first stage, the real input price w_t^N is taken as given, firms rent inputs H_{it}^N and Z_{it} in a perfectly competitive factor markets in order to minimize costs subject to the production constraint. Each firm maximizes profits:

$$\begin{aligned}\max_{\left\{Z_{it}, H_{it}^N\right\}} \; & mc_{it}^A X_{it}^A - w_t^A H_{it}^A - \Phi_Z\left(d_t, d_{t-1}\right) p_t^N Z_{it} \\ & + \lambda_t^A \left[\varepsilon_t^Z Z_{it}^{\omega} \left(\left(\Phi_X\left(d_t, d_{t-1}\right) \bar{L}_i\right)^{1-\sigma} \left(\kappa_i H_{it}^A\right)^{\sigma}\right)^{1-\omega} - X_{it}^A\right],\end{aligned}$$

under the supply constraint in eq. (C.23). The variable mc_{it}^A denotes the real marginal cost of producing an additional agricultural good.

The cost-minimization problem ensures that the real agricultural wage is directly driven by the marginal product of labour:

$$w_t^A = mc_t^A \left(1-\omega\right) \sigma \frac{X_t^A}{H_t^A}. \tag{C.26}$$

The second cost-minimizing condition is obtained from the marginal product of intermediate consumption Z_t and provides the optimal demand for intermediate goods from the farmer:

$$Z_t = \omega \frac{mc_t^A}{\Phi_Z \left(d_t, d_{t-1}\right) p_t^N} X_t^A. \tag{C.27}$$

In the second stage, the intermediate firm operates monopolistically and sets the retail price according to a Rotemberg (1982) technology. Intermediate good firms face adjustment costs with price changes AC_{it}^A defined according to:

$$AC_{it}^A = \frac{\kappa_A}{2} \left(\frac{P_{it}^A}{P_{it-1}^A} - (\pi_{t-1}^A)^{\xi_A} \right)^2,$$

where κ_A is the cost of adjusting prices, and ξ_A is the coefficient that measures the rate of indexation to the past rate of inflation of intermediate goods, $\pi_{t-1}^A = P_{t-1}^A / P_{t-2}^A$. These costs are paid in terms of the final goods at a market price of $P_{y,t}^N$. Given this price adjustment cost specification, the problem of the representative firms becomes dynamic:

$$\mathbb{E}_t \sum_{\tau=0}^{+\infty} \frac{\lambda_{t+\tau}^c}{\lambda_t^c} \beta^\tau \left[\frac{P_{it+\tau}^A}{P_{t+\tau}^C} X_{it+\tau}^A - mc_{it+\tau}^A X_{it+\tau}^A - p_{y,t+\tau}^N Y_{t+\tau}^A AC_{it+\tau}^A \right] = 0, \tag{C.28}$$

The variables mc_{it}^A and $p_{y,t}^A$ are the real marginal cost and the relative price of non-agricultural final goods, respectively. Since firms are owned by households, they discount expected profits using the same discount factor as households ($\beta^\tau \lambda_{t+\tau}^c / \lambda_t^c$).[13] The firm faces the downward sloping constraint from final good producers obtained from eq. (C.17):

$$X_{it}^A = \left(\frac{P_{it}^A}{P_t^A} \right)^{-\epsilon_A} X_t^A. \tag{C.29}$$

Anticipating symmetry between firms with $P_t^A = P_{it}^A$, first-order condition is:

$$\begin{aligned} &(1-\epsilon_A) p_t^A + \epsilon_A mc_t^A - p_{y,t}^N \frac{Y_t^A}{X_t^A} \kappa_A \left(\pi_t^A - (\pi_{t-1}^A)^{\xi_A} \right) \pi_t^A \\ &\quad + \kappa_A \beta \mathbb{E}_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} p_{y,t+1}^N \frac{Y_{t+1}^A}{X_t^A} \left(\pi_{t+1}^A - (\pi_t^A)^{\xi_A} \right) \pi_{t+1}^A \right\} = 0. \end{aligned} \tag{C.30}$$

[13]The stochastic discount factor is endogenously determined by the Euler condition of households. In equilibrium, the stochastic discount is inversely related to the real interest rate.

3.2.3 Non-Agricultural Intermediate Production

Each representative intermediate firm $i \in [0, n]$ has the following technology:

$$X_{it}^{N} = \varepsilon_t^{Z} H_{it}^{N}, \tag{C.31}$$

where X_{it}^{N} is the production of the i^{th} intermediate firm that combines labour demand H_{it} and technology ε_t^{Z}.

Intermediate goods producers solve a two-stage problem. In the first stage, the real input price w_t^{N} is taken as given, and these firms rent inputs H_{it}^{N} in a perfectly competitive factor markets in order to minimize costs subject to the production constraint:

$$\max_{\{X_{it}^{N}, H_{it}^{N}\}} mc_{it}^{N} X_{it}^{N} - w_t^{N} H_{it}^{N} + \lambda_t^{n} \left[X_{it}^{N} - \varepsilon_t^{Z} H_{it}^{N} \right]$$

The first-order condition leads to i) $mc_{it}^{N} = \lambda_t^{n}$ and ii) the real marginal cost expression:

$$mc_{it}^{N} = mc_t^{N} = \frac{w_t^{N}}{\varepsilon_t^{Z}}. \tag{C.32}$$

In the second stage, the intermediate firm operates monopolistically and sets the retail price according to a Rotemberg (1982) technology. Intermediate good firms face adjustment costs on price changes, AC_{it}^{N} defined according to:

$$AC_{it}^{N} = \frac{\kappa_N}{2} \left(\frac{P_{it}^{N}}{P_{it-1}^{N}} - (\pi_{t-1}^{N})^{\xi_N} \right)^2$$

where κ_N is the cost of adjusting prices and ξ_N is the coefficient that measures the rate of indexation to the past rate of inflation of intermediate goods $\pi_{t-1}^{N} = P_{t-1}^{N} / P_{t-2}^{N}$. These costs are paid in terms of final goods at a market price $P_{y,t}^{N}$. Given this price adjustment cost specification, the problem of the representative firms becomes dynamic:

$$\mathbb{E}_t \sum_{\tau=0}^{+\infty} \frac{\lambda_{t+\tau}^{c}}{\lambda_t^{c}} \beta^{\tau} \left[\frac{P_{it+\tau}^{N}}{P_{t+\tau}^{C}} X_{it+\tau}^{N} - \varepsilon_{t+\tau}^{N} mc_{iNont+\tau}^{N} X_{it+\tau}^{N} - p_{y,t+\tau}^{N} Y_{t+\tau}^{N} AC_{it+\tau}^{N} \right], \tag{C.33}$$

where ε_t^{N} is an AR(1) markup shock that aims at capturing the external factors driving the inflation rate, which are not included in the model such as commodity prices. The variables mc_{it}^{N} and $p_{y,t+\tau}^{N}$ are the real marginal cost and the relative price of non-agricultural final goods, respectively.

Firms operate in a monopolistically competitive market as in Dixit and Stiglitz (1977). Hence, the amount of firm-specific output, X_{it}^N, is demand-determined in response to its relative price P_{it}^N/P_t^N and to the aggregate demand for goods, X_t^N, as obtained from eq. (C.17):

$$X_{it}^N = \left(\frac{P_{it}^N}{P_t^N}\right)^{-\epsilon_N} X_t^N \,. \tag{C.34}$$

Anticipating symmetry between firms with $P_t^N = P_{it}^N$, the first-order condition reads:

$$\begin{aligned}(1-\epsilon_N)\, p_t^N + \epsilon_N \varepsilon_t^N mc_t^N - p_{y,t}^N \frac{Y_t^N}{X_t^N} \kappa_N \left(\pi_t^N - (\pi_{t-1}^N)^{\xi_N}\right) \pi_t^N \\ + \kappa_N \beta \mathbb{E}_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} p_{y,t+1}^N \frac{Y_{t+1}^N}{X_t^N} \left(\pi_{t+1}^N - (\pi_t^N)^{\xi_N}\right) \pi_{t+1}^N \right\} = 0\end{aligned} \tag{C.35}$$

3.3 Monetary Policy

The central bank reacts to fluctuations in price, activity and external imbalance. The general expression of the linear interest rule implemented by the central bank can be expressed as:

$$R_t = \left(\bar{R}\right)^{1-\rho} (R_{t-1})^{\rho} \left[(\pi_t)^{\phi_\pi} (RER_t)^{\phi_E}\right]^{(1-\rho)} \left(\mathcal{Y}_t^D/\mathcal{Y}_{t-1}^D\right)^{\phi_{\Delta Y}} \varepsilon_t^R, \tag{C.36}$$

where $\bar{R}$ is the steady-state interest rate, $\mathcal{Y}_t^D$ is gross domestic product, ε_t^R is an exogenous $AR(1)$ monetary policy shock,[14] ϕ_π, ϕ_E and $\phi_{\Delta Y}$ denote inflation, real exchange rate and GDP growth gap parameters, respectively, that aim to stabilize the economy when it deviates from its steady state. In a small economy context, we follow the definition of monetary policy rules in open economies of Clarida et al. (1998) and estimate ϕ_E. A positive value of ϕ_E induces a reduction in the variance of the real exchange rate.

3.4 Foreign Economy

Our foreign economy is characterized by a set of five equations that aims at capturing the standard business cycle patterns of the foreign economy. Four equations are taken from the standard New Keynesian framework, namely, the Phillips curve, the IS curve, the Taylor rule, and the CES substitution curve between two types of goods. These

[14] The monetary policy shock follows a standard $AR(1)$ stochastic process: $\varepsilon_t^R = (1-\rho_R) + \rho_R \varepsilon_{t-1}^R + \varepsilon_t^R$, with $\eta_t^R \sim \mathcal{N}(0, \sigma_R)$, and $0 \leq \rho_R < 1$ the autoregressive term.

equations provide the structural relations between aggregate output Y_t^*, agricultural output Y_t^{A*}, inflation π_t^* and the nominal interest rate R_t^*.

The first relation is the New Keynesian Phillips Curve that links current inflation (π_t^*) to expected inflation ($\mathbb{E}_t\pi_{t+1}^*$) and to the output gap (Y_t^*):

$$(1-\epsilon_N)+\epsilon_N\chi^* Y_t^* - \kappa^*\left(\pi_t^*-1\right)\pi_t^* + \kappa^*\beta\mathbb{E}_t\left\{\left(\pi_{t+1}^*-1\right)\pi_{t+1}^*\right\}=0 \tag{C.37}$$

In this expression, β is the psychological discount factor, χ^* is the Rotemberg price adjustment cost, and ϵ_N is the imperfect substitution between varieties. This relation comes from the aggregation of the supply decision of firms that have a market power and can optimize prices with adjustment costs generating nominal rigidities.

The second relation is the intertemporal (dynamic) IS curve. This schedule is a log-linearization of the Euler bond equation that describes the intertemporal allocation of consumption of agents in the economy over the cycles. This relation plays the same role as the IS curve in the IS-LM model by determining the output gap equation Y_t^* through:

$$\beta\mathbb{E}_t\left\{\frac{Y_t^*}{Y_{t+1}^*}\frac{1}{\pi_{t+1}^*}\right\}=\frac{\varepsilon_t}{R_t^*} \tag{C.38}$$

where ε_t^{Y*} is a demand shock characterized by an iid $AR(1)$. This time-preference shock lowers the discount factor and forces the foreign household to increase its spending in terms of consumption goods.

The third relation is the Taylor rule that links the nominal interest rate R_t^* controlled by monetary authorities to the average inflation rate (π_t^* and P_t^{A*}/P_{t-1}^{A*} with sectoral weight n) and to the output gap (Y_{t+1}^*). Monetary policy inertia is accounted for through the previous period rate of interest (R_{t-1}^*). This rule is defined as:

$$\beta R_t^* = \left(\beta R_{t-1}^*\right)^{\rho^*}\left(((\pi_t^*)^n\left(p_t^{A*}/p_{t-1}^{A*}\right)^{1-n})^{\phi_\pi^*}(Y_t^*/\bar{Y}^*)^{\phi_y^*}\right)^{(1-\rho^*)}. \tag{C.39}$$

In this expression, ρ^* is the autocorrelation parameter, ϕ_π^* is the elasticity of the nominal interest rate to the inflation rate, and ϕ_y^* is the elasticity of the nominal interest rate to the output gap. We multiply by β the interest rate to get a balanced steady state (as R^*=β^{-1}). In addition, p_t^{A*}/p_{t-1}^{A*} denotes the variations of the relative price index of agricultural goods.

The fourth equation determines the demand for agricultural goods by foreign households. This equation is a reduced-form equation modelling households preferences by substituting agricultural and non-agricultural goods *via*:

$$\frac{Y_t^{A*}}{Y_t^*} = \frac{\varphi}{1-\varphi}\left(\frac{p_t^{A*}}{p_{t-1}^{A*}}\right)^{-\mu},$$

where p_t^{A*} is the relative price between goods, parameter φ is the share of agricultural goods in the consumption basket, and μ is the substitution parameter as defined in eq. (C.2). This equation shows that the household's consumption allocation is determined by the gap between variations in the relative price index between agricultural and non-agricultural goods.

Finally, the foreign agricultural price is too volatile to be determined by a New Keynesian Phillips curve. We assume the relative price of foreign agricultural goods is determined by an AR(1) shock process:

$$\varepsilon_t^{A*} = 1 - \rho_A^* + \rho_A^* \varepsilon_{t-1}^{A*} + \eta_t^{A*} \text{ with } \eta_t^{A*} \sim \mathcal{N}(0, \sigma_A^{*2}), \tag{C.40}$$

with $p_t^{A*} = \varepsilon_t^{A*}$.

In addition, the second exogenous shock affecting the IS-curve reads:

$$\varepsilon_t^{Y*} = 1 - \rho_Y^* + \rho_Y^* \varepsilon_{t-1}^{Y*} + \eta_t^{Y*} \text{ with } \eta_t^{Y*} \sim \mathcal{N}(0, \sigma_Y^{*2}). \tag{C.41}$$

In the long run, the economies are perfectly symmetric with $\bar{Y}$=$\bar{Y}^*$, $\bar{Y}^A$=$\bar{Y}^{A*}$, $\bar{R}$=$\bar{R}^*$, π=π^* and p^A=p^{A*}.

3.5 Stochastic Shock Processes

To be in line with the seminal contribution of Smets and Wouters (2003), all our random processes $s = \{Z, N, D, R, Y^*, A^*\}$ follow an AR(1) specification defined by:

$$\varepsilon_t^s = \rho^s \varepsilon_{t-1}^s + \eta_t^s \text{ with } \eta_t^s \sim N(0, \sigma_s). \tag{C.42}$$

3.6 Shocks, Aggregation and Equilibrium Conditions

After (i) aggregating all agents and varieties in the economy, (ii) imposing market clearing on all markets, and (iii) substituting the relevant demand functions, we can deduct the general equilibrium conditions of the model.

First, total demand for non-agricultural goods is as follows:

$$Y_t^N = (1-\varphi)\left(\frac{P_{y,t}^N}{P_t^C}\right)^{-\mu} C_t + \Phi_B(b_{jt}^*) + AC_t^N Y_t^N + AC_t^A Y_t^A, \tag{C.43}$$

while the equilibrium in the intermediate goods market after aggregation is determined by:

$$nX_t^N = (1-\alpha_N)\left(\frac{P_t^N}{P_{y,t}^N}\right)^{-\mu_N} Y_t^N + \alpha_N \left(\frac{1}{e_t}\frac{P_t^N}{P_{y,t}^{N*}}\right)^{-\mu_N} Y_t^{N*} + (1-n)\,Z_t, \tag{C.44}$$

where $nX_t^N = \int_0^n X_{it}^N \,\mathrm{d}i$ is the aggregate supply, and $(1-n)\,Z_t = \int_n^1 Z_{it}\,\mathrm{d}i$ denotes the aggregate demand for domestic intermediate goods from farmers.

Similarly for the agricultural sector, the aggregate demand is:

$$Y_t^A = \varphi\left(\frac{P_{y,t}^A}{P_t^C}\right)^{-\mu} C_t, \tag{C.45}$$

and equilibrium in the intermediate market is achieved by the following clearing market condition:

$$(1-n)\,X_t^A = (1-\alpha_A)\left(\frac{P_t^A}{P_{y,t}^A}\right)^{-\mu_A} Y_t^A + \alpha_A \left(\frac{1}{e_t}\frac{P_t^A}{P_{y,t}^{A*}}\right)^{-\mu_A} Y_t^{A*}. \tag{C.46}$$

Turning to the labour market, the market clearing condition between household labour supply and demand from firms in each sector is:

$$\int_0^1 h_{jt}^N \mathrm{d}j = \int_0^n H_{it}^N \mathrm{d}i \text{ and } \int_0^1 h_{jt}^A \mathrm{d}j = \int_n^1 H_{it}^A \mathrm{d}i. \tag{C.47}$$

The law of motion for the total amount of real foreign debt is:

$$b_{jt}^* = \frac{R_{t-1}^*}{\pi_t^C}\Delta e_t b_{jt-1}^* + n\left(p_t^N X_t^N - p_{y,t}^N Y_t^N\right) + (1-n)\left(p_t^A X_t^A - p_{y,t}^A Y_t^A - p_t^X Z_t\right). \tag{C.48}$$

TABLE C.1: Notations of Variables and Parameters for the Household Block

Variable	Description
	Variables
C_{jt}	Consumption index
C_{jt}^N	Consumption of non-agricultural goods
C_{jt}^A	Consumption of agricultural goods
P_t^C	Consumption price index
P_t^{C*}	Foreign consumption price index
$P_{y,t}^N$	Price index of final non-agricultural goods
$P_{y,t}^A$	Price index of final agricultural goods
h_{jt}	labour disutility index
h_{jt}^N	Hours worked in the non-agricultural sector
h_{jt}^A	Hours worked in the agricultural sector
w_t^N	Real hourly wage in the non-agricultural sector
w_t^A	Real hourly wage in the agricultural sector
Π_{jt}	Profits generated by imperfect competition in goods in both sectors
b_{jt}	Domestic bonds
b_{jt}^*	Foreign bonds
R_t	Interest rate on domestic bonds
R_t^*	Interest rate on foreign bonds
π_t^C	Inflation rate of Consumption goods
e_t	Nominal exchange rate
$p_{y,t}^N$	Relative price of final non-agricultural goods wrt consumption price index
rer_t	Real exchange rate
λ_t^c	Marginal utility of consumption
	Parameters
μ	Substitution elasticity between the two goods
h	Consumption habits parameter
σ_C	Consumption risk aversion
σ_H	Labour disutility
φ	Share of agricultural goods in household consumption basket
n	Relative share of employment in the non-agricultural sector
ι	Hours worked sectoral adjustment cost
χ_B	International financial market cost
χ_N	Scale parameter in non-agricultural sector
χ_A	Scale parameter in agricultural sector

And the real GDP can be computed either by the demand side ($\mathcal{Y}_t^D$) or by the supply side ($\mathcal{Y}_t^S$):

$$\mathcal{Y}_t^D = np_{y,t}^N Y_t^N + (1-n)\, p_{y,t}^A Y_t^A \tag{C.49}$$

$$\mathcal{Y}_t^S = np_t^N X_t^N + (1-n)\left(p_t^A X_t^A - p_t^N Z_t\right). \tag{C.50}$$

Finally, the general equilibrium condition is defined as a sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and prices $\{\mathcal{P}_t\}_{t=0}^{\infty}$ such that for a given sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and the realization of shocks $\{\mathcal{S}_t\}_{t=0}^{\infty}$, the sequence $\{\mathcal{P}_t\}_{t=0}^{\infty}$, guarantees simultaneous equilibrium on all markets previously defined.

Table C.2: Notations of Variables and Parameters for the Final Firms Block

Variable	Description
	Variables
$P_{y,t}^N$	Consumption price index of goods produced in the non-agricultural sector
$P_{y,t}^A$	Consumption price index of goods produced in the agricultural sector
P_t^{C*}	Foreign consumption price index
P_t^N	Intermediate price of non-agricultural goods
P_t^A	Intermediate price of agricultural goods
X_t^N	Intermediate production of non-agricultural goods
X_t^A	Intermediate production of agricultural goods
$X_t^{N\star}$	Foreign intermediate goods in the non-agricultural sector
$X_t^{A\star}$	Foreign intermediate goods in the agricultural sector
Y_t^N	Final non-agricultural goods
Y_t^A	Final agricultural goods
	Parameters
α_N	Share of imports in the production of final non-agricultural goods
α_A	Share of imports in the production of final agricultural goods
ϵ_N	Elasticity of substitution between non-agricultural varieties
ϵ_A	Elasticity of substitution between agricultural varieties
μ_N	Elasticity of substitution between domestically produced and imported intermediate non-agricultural goods
μ_A	Elasticity of substitution between domestically produced and imported intermediate agricultural goods
n	Relative share of employment in the non-agricultural sector

4 Estimation

We apply standard Bayesian estimation techniques as in Smets and Wouters (2003,0). In this section, we describe the data sources and transformations.

4.1 Data

The model is estimated using 7 time series with Bayesian methods and quarterly data for New Zealand over the sample time period 1989:Q1 to 2014:Q2. All data is in log-difference except interest rate and climate. The time reference for all indexes is 2010:Q1. Transformed data is shown in fig. C.3.

- **Gross domestic product**: real per capita output, expenditure approach, seasonally adjusted. *Source:* Statistics New Zealand.
- **CPI inflation**: all groups index, *Source:* Statistics New Zealand.
- **Agricultural output**: real agriculture, fishing and forestry gross domestic product, seasonally adjusted. *Source:* Statistics New Zealand.

Table C.3: Notations of Variables and Parameters for the Intermediate-good Firms Block

Variable	Description
	Variables
AC_{it}^N	Adjustment costs faced by non-agricultural intermediate good firms
d_t	Weather damage variable
H_{it}^N	labour demand in non-agricultural intermediate good firms
H_{it}^A	labour demand in agricultural intermediate good firms
$\bar{L}_i$	Land endowment
mc_t^N	Marginal cost in the non-agricultural sector
mc_t^A	Marginal cost in the agricultural sector
P_t^C	Consumption price index
P_t^N	Intermediate price index of non-agricultural goods
P_t^A	Intermediate price index of agricultural goods
w_t^N	Real hourly wage in the non-agricultural sector
w_t^A	Real hourly wage in the agricultural sector
p_t^N	Relative price of intermediate non-agricultural goods wrt consumption price index
p_t^A	Relative price of intermediate agricultural goods wrt consumption price index
X_t^N	Intermediate non-agricultural goods
X_t^A	Intermediate agricultural goods
Z_{it}	Non-agricultural input in the agricultural production
η_t^W	Weather shock
$\tilde{\eta}_{t-1}^W$	News shock (weather shock observed in advance)
ε_t^W	Drought index
ε_t^Z	Technology shock hitting the agricultural production function
π_t^N	Inflation rate of production price of non-agricultural goods
π_t^A	Inflation rate of production price of non-agricultural goods
	Parameters
β	Discount factor
γ_O^X, γ_1^X	Parameters of the contemporaneous and lagged effects of the weather damage, respectively (for the damage function directly hitting the agricultural production function)
γ_O^Z, γ_1^Z	Parameters of the contemporaneous and lagged effects of the weather damage, respectively (for the damage function affecting the demand for inputs)
ϵ_N	Elasticity of substitution between non-agricultural varieties
ϵ_A	Elasticity of substitution between agricultural varieties
κ_N	Cost of adjusting prices for non-agricultural intermediate firms
κ_A	Cost of adjusting prices for agricultural intermediate firms
κ_i	Technology scale parameter in the agricultural intermediate good firm
ξ^N	Rate of indexation of the past rate of inflation of intermediate non-agricultural goods
ξ^A	Rate of indexation of the past rate of inflation of intermediate agricultural goods
ρ_W	Autoregressive parameter capturing the persistence of a drought
ρ_d	Autoregressive parameter capturing the persistence of the damages of the drought
σ	Share of production/land in the production process of agricultural goods
ω	Elasticity of output to intermediate input in agricultural intermediate good firms

- **Agricultural producer price inflation**: agriculture, fishing and forestry producer price index. *Source:* Statistics New Zealand.
- **Population**: actual population of working age, in thousands, seasonally adjusted. *Source:* Statistics New Zealand.
- **Interest rate**: 3-Month rates and yields: bank bills for New Zealand, not seasonally adjusted. *Source:* Main Economic Indicators, OECD.

TABLE C.4: Notations of Variables and Parameters for Remaining Blocks

Variable	Description
	Variables
p_t^{A*}	Relative price index of foreign agricultural goods
R_t	Nominal interest rate
R_t^*	Nominal foreign interest rate
$\bar{R}$	Steady-state interest rate
$\bar{R}^*$	Steady-state foreign interest rate
rer_t	Real exchange rate
$\mathcal{Y}_y^D$	Gross domestic product (demand side)
Y_t^*	Aggregate foreign output
Y_t^{A*}	Aggregate foreign agricultural output
ϵ_t^R	Monetary policy shock
$\epsilon_t^{Y^*}$	Foreign demand shock
π_t^*	Foreign inflation rate
	Parameters
β	Discount factor
ϵ_N	Elasticity of substitution between non-agricultural varieties
ϵ_A	Elasticity of substitution between agricultural varieties
μ	Substitution elasticity between the two types of goods
ϕ_π	Inflation reaction parameter
ϕ_π^*	Foreign inflation reaction parameter
ϕ_E	Real exchange rate reaction parameter
$\phi_{\Delta Y}$	Output-gap growth reaction parameter
ϕ_y^*	Elasticity of the nominal interest rate to the output gap (for foreign authorities)
κ^*	Cost of adjusting prices in foreign firms
rho^*	Foreign Taylor rule smoothing parameter
φ	Share of agricultural goods consumed in total consumption
n	Relative share of employment in the non-agricultural sector

- **Real exchange rate**: real trade weighted index. *Source:* Reserve Bank of New Zealand.
- **Climate**: soil moisture deficit at the station level. *Source:* National Climate Database, National Institute of Water and Atmospheric Research.

4.1.1 The Weather Measure

The measure of weather we use is an index of drought constructed following the methodology of Kamber et al. (2013). It is based on soil moisture deficit observations[15] and is collected from the National Climate Database from National Institute of Water and Atmospheric Research. Raw data is obtained from weather stations at a monthly rate. The spatial covering of these stations is depicted in fig. C.2(a), while its temporal covering is represented in fig. C.2(b). To get quarterly national representative data, both spatial and time scales need to be changed. In a first step, we average the monthly values of mean soil moisture deficit at the region level. We then remove a seasonal

[15]Named “MTHLY: MEAN DEFICIT (WBAL)” in the database.

trend by simply subtracting long term monthly statistics. Long term statistics are evaluated as the average value over the 1980 to 2015 period. Then, we follow Narasimhan and Srinivasan (2005) to create the soil moisture deficit index. In a nutshell, for each $m = \{1, \ldots, 12\}$ month in each $t = \{1980, \ldots, 2015\}$ year, we compute monthly soil water deficit (expressed in percent) as:

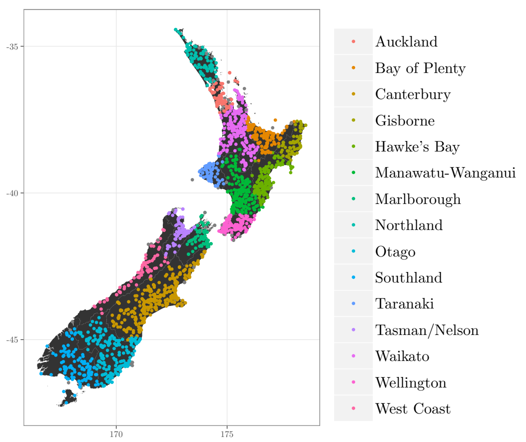
$$SD_{t,m} = \frac{SW_{t,m} - Med(SW_m)}{Med(SW_m)}. \tag{C.51}$$

The index for any given month is then computed as:

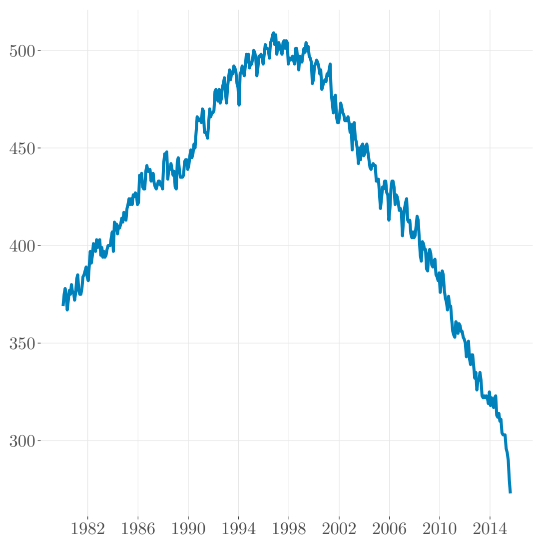
$$SMDI_{t,m} = 0.5 \times SMDI_{t,m-1} + \frac{SD_{t,m}}{50}, \tag{C.52}$$

using $SMDI_{1980,m} = \frac{SD_{1980,m}}{50}, \quad m = \{1, \ldots, 12\}$ as initial values for the series.

Then, we aggregate the monthly values of the index at the national level by means of a weighted mean, where the weights reflect the share of yearly agricultural GDP of each region.[16] In a final step, monthly observations are quarterly aggregated.



(a) Spatial covering



(b) Temporal covering

FIGURE C.2: Covering of Weather Stations Used to Construct the Soil Moisture Deficit Index

[16]The regional agricultural GDP data we use ranges from 1987 to 2014. The weight before 1987 and after 2014 is set to the average contribution of the region to the total agricultural GDP over the whole covered period.

4.1.2 The Climate Scenarios

To estimate the variability of the weather process η_t^W, we rely on simulated weather data from a circulation climate model, the Community Climate System Model (CCSM). We consider the data simulated under the four well-employed Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). They are given on a $0.9° \times 1.25°$ grid, at a monthly rate, for two distinct periods. The first one corresponds to "historical" values, and ranges from 1850 to 2005. The second one gives observations for "future" values up to 2100. Since our DSGE models is fed-up with quarterly data at the national level, we need to aggregate the raw data provided by the CCSM. To do so, we compute the average values of total rainfall at the region level by means of a weighted mean. The weight put on each cell of the grid in a given region is the proportion of the region covered by the cell. Values are then averaged for each month, at the national level. The aggregation is done using a weighted mean, where weights are set according to the share of agricultural GDP of the region.[17] Resulting data is then converted to quarterly data, by summing the monthly values of total rainfall. The final dataset of simulated data contains quarterly data of rainfall at the national level for the historical period (ranging from 1983 to 2005) and for the future period (covering 2006 to 2100) for each RCP scenario.

We then need to estimate how the variance of the weather shock changes through time in each of the $i = \{\text{RCP 2.6}, \text{RCP 4.5}, \text{RCP 6.0}, \text{RCP 8.5}\}$ scenario. We proceed by rolling window regression, the size of each window being set to 102 quarters, matching the size of the number of observations used to estimate the DSGE model. In each step of the rolling window regression, we fit an $AR(1)$ model to the data and compute the standard deviation of the residuals. We estimate the growth rate of the standard deviation $\Delta\sigma_{i,\varepsilon^W}$ by least squares, regressing the natural logarithm of the standard deviation previously obtained on time. Then, we estimate the average growth rate $\overline{\Delta\sigma_{i,\varepsilon^W}}$ of the standard deviation over the 1989–2100 period for the i^{th} scenario as:

$$\overline{\Delta\sigma_{i,\varepsilon^W}} = (1 + \sigma_{i,\varepsilon^W})^q - 1, \tag{C.53}$$

where σ_{i,ε^W} is the estimated compound quarterly rate of growth for the standard error of the weather shock process under the i^{th} climate change scenario, and q is the number of quarter in the whole sample, *i.e.*, 347. table C.5 summarizes the estimates.

[17] The regional agricultural GDP data we use ranges from 1987 to 2014. The weight before 1987 and after 2014 is set to the average contribution of the region to the total agricultural GDP over the whole covered period.

TABLE C.5: Estimations of Growth Rates of Standard Errors of the Weather Process Under Different Scenarios

Scenario	Compound quarterly rate (σ_{i,ε^W})	Average growth rate ($\overline{\Delta\sigma_{i,\varepsilon^W}}$)
RCP 2.6	-0.1271890×10^3	-4.269057
RCP 4.5	0.1897154×10^3	6.722968
RCP 6.0	0.2581432×10^3	9.256886
RCP 8.5	0.6176223×10^3	23.587480

Notes: For each Representative Concentration Pathways, we estimate the quarterly rate of growth of the standard deviation of the weather measure (σ_{i,ε^W}), and the corresponding average growth rate over the whole 1989–2100 period ($\overline{\Delta\sigma_{i,\varepsilon^W}}$).

4.1.3 Macroeconomic Time Series Transformation

Concerning the transformation of series, the point is to map non-stationary data to a stationary model (namely, here, GDP $\mathcal{Y}_t$). The data that are known to have a trend or unit root are made stationary in two steps. First, we divide the sample by the civilian population, denoted $\mathcal{N}_{i,t}$. Second, data are taken in log and we use a first difference filtering to obtain growth rates. Real variables are deflated by GDP deflator price index denoted $\mathcal{P}_t$.

As an illustration, the calculation method used to detrend real GDP growth per capita is as follows:

$$\Delta\widehat{\mathcal{Y}}_t^{rl} = \log\left(\frac{\widehat{\mathcal{Y}}_t}{\hat{\mathcal{P}}_t\mathcal{N}_t}\right) - \log\left(\frac{\widehat{\mathcal{Y}}_{t-1}}{\hat{\mathcal{P}}_{t-1}\mathcal{N}_{t-1}}\right),$$

where X_t^r, X_t^l, and $\widehat{X}_t$ denote the real, the per capita, and the log value of X_t, respectively.

Hours worked are divided by civilian population to improve the identification of labour demand, as in Smets and Wouters (2007):

$$\widehat{\mathcal{H}}_t^l = \log(\mathcal{H}_t) - \log(\mathcal{N}_t)$$

Turning to the weather index, we simply apply the logarithm function:

$$\widehat{\mathcal{S}}_t = \log(SMDI_t)$$

Finally, we demean the data because we do not incorporate trends in our model. We are aware that the introduction of trends could affect our estimation results. However for tractability reasons, we have chosen to focus on short run macroeconomic fluctuations and to neglect long run effects involved with trends. Such an approach has also been chosen by Smets and Wouters (2003).

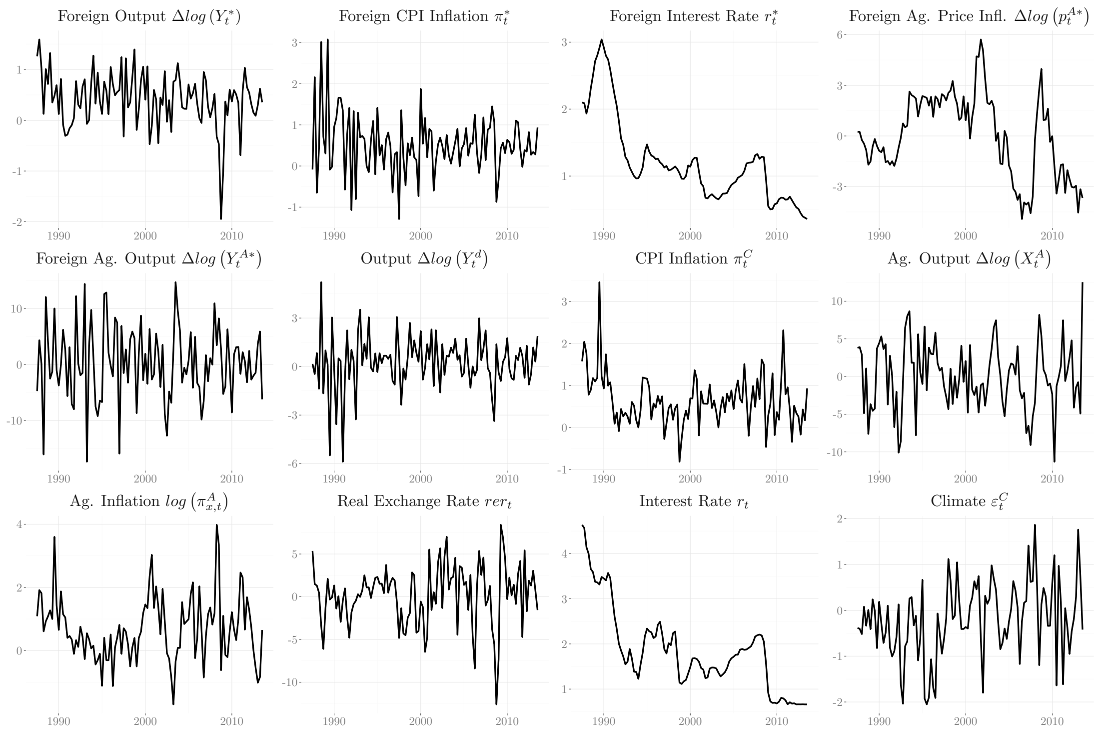


FIGURE C.3: Observable Variables Used in the BSVAR and the DSGE Estimations

4.2 Measurement Equations of the DSGE Model

The final dataset includes ten times series: real *per capita* growth rate of the GDP (demand side) $\Delta\widehat{\mathcal{Y}}_t^{rl}$, real capita growth rate of agricultural output $\Delta\widehat{\mathcal{Y}}_t^{Arl}$, per capita hours worked $\widehat{\mathcal{H}}_t^l$, as well as quarterly money market rate $\mathcal{R}_t$ (on an annual basis), inflation rate $\Delta\hat{\mathcal{P}}_t$, inflation rate for agricultural goods $\Delta\hat{\mathcal{P}}_t^A$, and a weather index $\widehat{\mathcal{S}}_t$. fig. C.3 plots the transformed data.

Measurement equations read as follows:

$$\begin{bmatrix} 100{*}\widehat{\mathcal{H}}_t^l \\ 100{*}\Delta\widehat{\mathcal{Y}}_t^{rl} \\ 100{*}\Delta\widehat{\mathcal{P}}_t \\ 100{*}\Delta\widehat{\mathcal{Y}}_t^{Arl} \\ 100{*}\Delta\widehat{\mathcal{P}}_t^A \\ 100{*}\widehat{\mathcal{S}}_t \\ 100{*}\mathcal{R}_t \end{bmatrix} = \begin{bmatrix} n\log(h_t^N/\bar{h}^N) + (1-n)\log(h_t^A/\bar{h}^A) \\ \log(\mathcal{Y}_t^D/\mathcal{Y}_{t-1}^D) \\ \log(\pi_t) \\ \log(X_t^A/X_{t-1}^A) \\ \log(\pi_{y,t}^A) \\ \log(\varepsilon_t^S) \\ (R_t - \bar{R}) \end{bmatrix}.$$

5 The Non-Linear Model

5.1 Equations Summary

The marginal utility of consumption is given by:

$$\lambda_t^C = \exp\left(\frac{\sigma_C - 1}{1+\sigma_H} {h_t}^{1+\sigma_H}\right) (C_t - h\, C_{t-1})^{(-\sigma_C)}.$$

The Euler equation is given by:

$$\lambda_t^C = \beta\, \lambda_{t+1}^C \frac{r_t}{\pi_{t+1}}.$$

The real exchange rate is obtained by:

$$RER_t = \Delta e_t \frac{\pi_t^*}{\pi_t} RER_{t-1}.$$

Variations of the expected nominal exchange rate is obtained by:

$$\Delta e_{t+1} = \frac{r_t}{r_t^*} \left(1 + \chi_B\, p_{y,t}^N\, b_t^*\right).$$

The labour supply equation in each sector is:

$$w_t^N = (c_t - h\, c_{t-1}) \frac{n}{\chi_N} {h_t}^{\sigma_H} \left(\frac{{h^N}_t}{h_t}\right)^{\iota},$$
$$w_t^A = {h_t}^{\sigma_H} (c_t - h\, c_{t-1}) \frac{1-n}{\chi_A} \left(\frac{{h^A}_t}{h_t}\right)^{\iota}.$$

The labour effort disutility index generating costly cross-sectoral labour re-allocation:

$$h_t^{1+\iota} = n\, (h_t^N)^{1+\iota} + (1-n)\, (h_t^A)^{1+\iota}.$$

Non-agricultural and agricultural production functions are given by:

$$X_t^N = {h^N}_t\, \varepsilon_t^Z,$$
$$X_t^A = \varepsilon_t^Z\, {Z_t}^{\omega} \left(\left(\left(1 + \gamma_0^X\, D_t + \gamma_1^X\, D_{t-1}\right)\, \bar{L}\right)^{1-\sigma} \left({h^A}_t\, \kappa\right)^{\sigma}\right)^{1-\omega}.$$

Real marginal products of labour determining the real wage for each sector are:

$$
\begin{aligned}
w_t^N &= X_t^N \, \frac{mc_t^N}{h^N{}_t}, \\
w_t^A &= \frac{X_t^A \, \sigma \, (1-\omega) \; mc_t^A}{h^A{}_t}.
\end{aligned}
$$

Real marginal product of intermediate goods is:

$$
Z_t = \frac{X_t^A \, \omega \, mc_t^A}{\left(1 + \gamma_0^Z d_t \, + \gamma_1^Z d_{t-1} \,\right) \, p_t^N}.
$$

The Rotemberg sticky price device:

$$
\begin{aligned}
X_t^N \, n \, p_{x,t}^N \, (1-\epsilon_N) + X_t^N \, n \, mc_t^N \, \epsilon_N \, \varepsilon_t^N - \kappa_N \, p_{y,t}^N \, \pi_t^N \, \left(\pi_t^N - (\pi_{t-1}^N)^{\xi_N}\right) \, y_t^N \\
+ \, \kappa_N \beta \frac{\lambda_{t+1}^C}{\lambda_t^C} \, p_{y,t+1}^N \, \pi_{t+1}^N \left(\pi_{t+1}^N - (\pi_t^N)^{\xi_N}\right) \, y_{t+1}^N = 0
\end{aligned}
$$

The Rotemberg sticky price device for the other sector:

$$
\begin{aligned}
X_t^A \, (1-n) \, (1-\epsilon_A) \, p_{x,t}^A + X_t^A \, (1-n) \, mc_t^A \, \epsilon_A - \kappa_A p_{y,t}^N \pi_t^A \, \left(\pi_t^A - (\pi_{t-1}^A)^{\xi_A}\right) \, y_t^A \\
+ \kappa_A \beta \frac{\lambda_{t+1}^C}{\lambda_t^C} \, p_{y,t+1}^N \pi_{t+1}^A \, \left(\pi_{t+1}^A - (\pi_t^A)^{\xi_A}\right) \, y_{t+1}^A = 0
\end{aligned}
$$

The intermediate goods equilibrium on each sector:

$$
\begin{aligned}
n \, X_t^N &= y_t^N \, (1-\alpha_N) \left(\frac{p_t^N}{p_{y,t}^N}\right)^{-\mu_N} + \alpha_N \left(\frac{p_t^N}{RER_t}\right)^{-\mu_N} y_t^* + (1-n) \, Z_t, \\
(1-n) \, X_t^A &= y_t^A \, (1-\alpha_A) \left(\frac{p_t^A}{p_{y,t}^A}\right)^{-\mu_A} + \alpha_A \left(\frac{p_t^A}{\varepsilon_t^{A*}} \frac{1}{RER_t}\right)^{-\mu_A} y_t^{A*}
\end{aligned}
$$

Relative production and final price indexes are respectively given by:

$$
\begin{aligned}
\frac{p_t^N}{p_{t-1}^N} &= \frac{\pi_t^N}{\pi_t}, \\
\frac{p_t^A}{p_{t-1}^A} &= \frac{\pi_t^A}{\pi_t}, \\
\frac{p_{y,t}^N}{p_{y,t-1}^N} &= \frac{\pi_{y,t}^N}{\pi_t}, \\
\frac{p_{y,t}^A}{p_{y,t-1}^A} &= \frac{\pi_{y,t}^A}{\pi_t},
\end{aligned}
$$

while CES price indexes for final goods in real terms are:

$$p_{y,t}^{N\;1-\mu_N} = (1-\alpha_N)\; p_t^{N\,1-\mu_N} + \alpha_N\, RER_t^{\;1-\mu_N},$$
$$p_{y,t}^{A\;1-\mu_A} = (1-\alpha_A)\; p_t^{A\,1-\mu_A} + \alpha_A\, \left(RER_t\, p_t^{A*}\right)^{1-\mu_A},$$

and the consumption price index in real terms:

$$1 = (1-\varphi)\; p_{y,t}^{N\;1-\mu} + \varphi\, p_{y,t}^{A\;1-\mu},$$

and the law of motion of net foreign assets:

$$b_t^* = \Delta e_t \frac{r_{t-1}^*}{\pi_t}\, b_{t-1}^* + n\, X_t^N\, p_t^N - p_{y,t}^N\, y_t^N$$
$$- Z_t\,(1-n)\, p_t^N + (1-n)X_t^A\; p_t^A - y_t^A\, p_{y,t}^A,$$

which allows us to get the quarterly current account, computed as the variations of the external assets position:

$$ca_t = b_t^* - b_{t-1}^*.$$

The resource constraint for final goods is given by:

$$y_t^N \;=\; (1-\varphi)\; p_{y,t}^{N\;-\mu} c_t + y_t^N\, \kappa_N\, 0.5\, \left(\pi_t^N - \pi_{t-1}^{N\;\;\xi_N}\right)^2$$
$$+\, 0.5\kappa_A \left(\pi_t^A - \pi_{t-1}^{A\;\;\xi_A}\right)^2 y_t^A + 0.5\chi_B (b_t^*)^2,$$

and for agricultural goods:

$$y_t^A = \varphi\, \varepsilon_t^D\, p_{y,t}^{A\;-\mu} c_t.$$

The two-sector set-up allows us to disentangle GDP computation by the demand and the supply side:

$$\mathcal{Y}_t^D = p_{y,t}^N\, y_t^N + p_{y,t}^A y_t^A,$$
$$\mathcal{Y}_t^S = n p_t^N x_t^N + (1-n)(p_t^A x_t^A - p_t^N Z_t).$$

The damage law of motion is given by:

$$d_t = \rho_d d_{t-1} + log\left(\varepsilon_t^S\right).$$

The interest rate monetary policy rule:

$$log\left(\frac{r_t}{\bar{r}}\right) = \rho\, log\left(\frac{r_{t-1}}{\bar{r}}\right) + (1-\rho)\left(\phi_y\, log\left(\frac{y_t^d}{\bar{y}^d}\right) + \phi_\pi\, log\left(\pi_t\right)\right) + \phi_E\, log\left(RER_t\right) + \phi_{\Delta y}\, log\left(\frac{y_t^d}{y_{t-1}^d}\right) + log\left(\varepsilon_t^R\right)$$

The foreign economy structural equations are given by (i) the following Euler equation:

$$\frac{y_{t+1}^*}{y_t^*} = \beta\,\frac{r_t^*}{\pi_{t+1}^*}\frac{1}{\varepsilon_t^{Y*}},$$

as well as (ii) the following supply equation:

$$1-\epsilon_N + \epsilon_N\,\chi^* y_t^* - \kappa^*\left(\pi_t^* - 1\right)\pi_t^* + \beta\,\kappa^*\,\pi_{t+1}^*\left(\pi_{t+1}^* - 1\right) = 0,$$

(iii) the following monetary policy equation:

$$\log\left(\beta\, r_t^*\right) = \rho^*\,\log\left(\beta\, r_{t-1}^*\right) + (1-\rho^*)\,\phi_\pi^*\left(n\,\log\left(\pi_t^*\right) + (1-n)\,\log\left(\frac{\varepsilon_t^{A*}}{\varepsilon_{t-1}^{A*}}\right)\right) + (1-\rho^*)\,\phi_y^*\,\log\left(\frac{y_t^*}{\bar{y}^*}\right),$$

(iv) the following substitution equation determining the demand for agricultural goods:

$$\frac{y_t^{A*}}{y_t^*} = \frac{\varphi}{1-\varphi}\left(\frac{p_t^{A*}}{p_{t-1}^{A*}}\right)^{-\mu},$$

and (v), two stochastic shock processes:

$$\varepsilon_t^{A*} = 1 - \rho_A^* + \rho_A^*\varepsilon_{t-1}^{A*} + \eta_t^{PA*},$$
$$\varepsilon_t^{Y*} = 1 - \rho_Y^* + \rho_Y^*\,\varepsilon_{t-1}^{Y*} + \eta_t^{Y*}$$

6 Business Cycle Facts About Climate Shocks

To observe how the economy responds to a weather shock, we develop an empirical framework, a Bayesian Structural VAR, and analyze the impulse response functions following a drought shock.

6.1 Modeling Framework

Let us consider three blocks of equations: a first one representing a domestic small open economy, a second one representing domestic weather and a third one representing the international economy. The model writes:

$$\begin{bmatrix} A^{11} & A^{12} & A^{13} \\ 0 & A^{22} & 0 \\ 0 & 0 & A^{33} \end{bmatrix} \begin{bmatrix} X_t^D \\ X_t^W \\ X_t^* \end{bmatrix} = \sum_{l=1}^{p} \begin{bmatrix} B_l^{11} & B_l^{12} & B_l^{13} \\ 0 & B_l^{22} & 0 \\ 0 & 0 & B_l^{33} \end{bmatrix} \begin{bmatrix} X_{t-l}^D \\ X_{t-l}^W \\ X_{t-l}^* \end{bmatrix} + CI_t + \begin{bmatrix} \eta_t^D \\ \eta_t^W \\ \eta_t^* \end{bmatrix}, \tag{C.54}$$

where $t = 1, \ldots, T$ is the time subscript, p is the lag length,[18] X_t^D, X_t^W and X_t^* are column vectors of variables for the small open economy, the climatic block and the rest of the world respectively. The column vector I_t contains the j exogenous variables, including the constant. The error terms η_t^D, η_t^W and η_t^* are exogenous and independent with zero mean and variance σ^{η^D}, σ^{η^W}, and σ^{η^*}, respectively. The coefficients in A^{11} to A^{33}, B_l^{11} to B_l^{33}, and C are the parameters of interest.

For our New Zealand economy model, the domestic block is:

$$X_t^D = \left[\Delta log\left(Y_t^d\right) \quad \pi_t^C \quad \Delta log\left(X_t^A\right) \quad \log\left(\pi_{x,t}^A\right) \quad rer_t \quad r_t\right]',$$

where $\Delta log\left(Y_t^d\right)$ is for real GDP growth, π_t^C for prices, $\Delta log\left(X_t^A\right)$ and $\log\left(\pi_{x,t}^A\right)$ for agricultural real output growth and prices, respectively, rer_t for the nominal exchange rate, and r_t for interest rate. The weather block writes:

$$X_t^W = \left[\varepsilon_t^W\right]';$$

where ε_t^W is the weather measure, *i.e.*, the drought index. Finally, the international economy block writes:

$$X_t^* = \left[\Delta log\left(Y_t^*\right) \quad \pi_t^* \quad r_t^*\right]',$$

where $\Delta log\left(Y_t^d\right)$ stands for foreign real output growth, π_t^* for foreign prices and r_t^* for foreign interest rate.

[18] We use a lag of four in the model basing our choice on the value of the Akaike information criterion.

The framework represented by eq. (C.54) imposes bloc exogeneity (see e.g. Cushman and Zha (1997); Kim and Roubini (2000)). To be consistent with the small open economy setup, variables from the foreign economy block can impact variables from the domestic block, but not the other way around. In addition, we impose restrictions regarding the weather block, such that weather shocks may impact the domestic economy only.

For clarity purposes, eq. (C.54) can be rewritten in the following way:

$$AX_t = \sum_{l=1}^{p} B_l X_{t-l} + CI_t + \eta_t, \tag{C.55}$$

where $A = \begin{bmatrix} A^{11} & A^{12} & A^{13} \\ 0 & A^{22} & 0 \\ 0 & 0 & A^{33} \end{bmatrix}$ is the $n \times n$ matrix of contemporaneous effects with n the number of endogenous variables, $X_t = \begin{bmatrix} X_t^D & X_t^W & X_t^* \end{bmatrix}'$ is the $n \times 1$ vector of endogenous variables at time t, $B_l = \begin{bmatrix} B_l^{11} & B_l^{12} & B_l^{13} \\ 0 & B_l^{22} & 0 \\ 0 & 0 & B_l^{33} \end{bmatrix}$, for $l = 1, \ldots, p$ are the $n \times n$ matrices of lagged parameters to be estimated, C is the $n \times j$ matrix of parameters associated with the exogenous variables, and $\eta_t = \begin{bmatrix} \eta_t^D & \eta_t^W & \eta_t^* \end{bmatrix}'$, the $n \times 1$ vector contains white noise structural errors, normally distributed with zero mean and both serially and mutually uncorrelated. The model of eq. (C.55) can be written in a more compact way:

$$AX_t = BZ_t + \eta_t, \tag{C.56}$$

where $B = \begin{bmatrix} B_1 & \cdots & B_p & C \end{bmatrix}$ is the $n \times (np + j)$ matrix of lagged restrictions and $Z_t = \begin{bmatrix} X_{t-1} & \cdots & X_{t-p} & I_t \end{bmatrix}'$, is the $(np+j) \times 1$ column vector of lagged endogenous variables.

Restrictions imposed on contemporaneous relationships (A matrix) are summarized in table C.6, while those imposed on lagged relationships (B_l matrix) are reported in table C.7. These restrictions ensure the block exogeneity. Additional restrictions are set following Buckle et al. (2007). In both tables, structural equations are written in columns so that the lines show the variables appearing in each equation.

Table C.6: Contemporaneous Structure of the Model

Independent Variables	Dependent Variable: $\Delta log\left(Y_t^*\right)$	π_t^*	r_t^*	$\Delta log\left(Y_t^d\right)$	π_t^C	$\Delta log\left(X_t^A\right)$	$log\left(\pi_{x,t}^A\right)$	rer_t	r_t	ε_t^W
$\Delta log\left(Y_t^*\right)$	a11	a12	a13	0	0	0	0	a18	0	0
π_t^*	0	a22	a23	0	a25	0	a27	a28	0	0
r_t^*	0	0	a33	0	0	0	0	a38	a39	0
$\Delta log\left(Y_t^d\right)$	0	0	0	a44	0	0	0	a48	0	0
π_t^C	0	0	0	0	a55	0	0	a58	a59	0
$\Delta log\left(X_t^A\right)$	0	0	0	0	0	a66	0	a68	0	0
$log\left(\pi_{x,t}^A\right)$	0	0	0	0	0	0	a77	a78	a79	0
rer_t	0	0	0	0	a85	0	a87	a88	0	0
r_t	0	0	0	0	0	0	0	a98	a99	0
ε_t^W	0	0	0	a104	0	a106	0	a108	a109	a1010

Note: Structural equations are written in columns. Zeros represent contemporaneous restrictions imposed in matrix A from eq. (C.55). $\Delta log\left(Y_t^*\right)$: Foreign Output, π_t^*: Foreign CPI Inflation, r_t^*: Foreign Interest Rate, $\Delta log\left(Y_t^d\right)$: Output, π_t^C: CPI Inflation, $\Delta log\left(X_t^A\right)$: Ag. Output, $log\left(\pi_{x,t}^A\right)$: Ag. Inflation, rer_t: Real Exchange Rate, r_t: Interest Rate, ε_t^W: Climate.

Table C.7: Lagged Structure of the Model

Independent Variables	Dependent Variable: $\Delta log\left(Y_t^*\right)$	π_t^*	r_t^*	$\Delta log\left(Y_t^d\right)$	π_t^C	$\Delta log\left(X_t^A\right)$	$log\left(\pi_{x,t}^A\right)$	rer_t	r_t	ε_t^W
$\Delta log\left(Y_t^*\right)$	b11	b12	b13	b14	0	b16	0	b18	0	0
π_t^*	b21	b22	b23	0	b25	0	b27	b28	0	0
r_t^*	b31	b32	b33	0	0	0	0	b38	b39	0
$\Delta log\left(Y_t^d\right)$	0	0	0	b44	0	b46	0	b48	0	0
π_t^C	0	0	0	0	b55	0	b57	b58	b59	0
$\Delta log\left(X_t^A\right)$	0	0	0	b64	0	b66	0	b68	0	0
$log\left(\pi_{x,t}^A\right)$	0	0	0	0	b75	0	b77	b78	b79	0
rer_t	0	0	0	b84	b85	b86	b87	b88	0	0
r_t	0	0	0	0	0	0	0	b98	b99	0
ε_t^W	0	0	0	b104	b105	b106	b107	b108	b109	b1010

Note: Structural equations are written in columns. Zeros represent lagged restrictions imposed in matrix B_l from eq. (C.55). $\Delta log\left(Y_t^*\right)$: Foreign Output, π_t^*: Foreign CPI Inflation, r_t^*: Foreign Interest Rate, $\Delta log\left(Y_t^d\right)$: Output, π_t^C: CPI Inflation, $\Delta log\left(X_t^A\right)$: Ag. Output, $log\left(\pi_{x,t}^A\right)$: Ag. Inflation, rer_t: Real Exchange Rate, r_t: Interest Rate, ε_t^W: Climate.

6.1.1 The Foreign Economy Block

The foreign economy block comprises three variables: real output $\Delta log\left(Y_t^*\right)$, prices π_t^*, and interest rate r_t^*. All three measures are computed as a weighted average of the respective value observed for New Zealand's most important historical trading partners: Australia, United States, United Kingdom and Japan. Weights are fixed according to the share of imports and exports with New Zealand at each quarter.

We follow Rohe and Hartermann (2015) and restrict the foreign structural equations in a recursive order to guarantee the block structure of the contemporaneous matrix. Prices respond to contemporaneous variations of output. They also respond to variations in interest rate, but only with a lag. Interest rate is assumed to be affected by both output and prices movements.

6.1.2 The Domestic Climate Block

The VAR model estimated contains a domestic weather block to study the impact of climatic conditions on business cycle fluctuations. We rely on the same weather variable as in the DSGE model whose construction is explained in appendix 4.1.1. When it takes positive values, the weather variable depicts a prolonged episode of dryness. It is the only variable in the exogenous domestic weather block and it is assumed to have significant contemporaneous effects on GDP growth, agricultural output growth, real exchange rate and interest rate. No restrictions are set for lagged effects except those ensuring the exogeneity between blocks.

6.1.3 The Domestic Economy Block

The domestic economy block comprises real output growth $\Delta\left(Y_t^d\right)$, prices π_t^C, real agricultural output growth $\Delta log\left(X_t^A\right)$, agricultural prices $log\left(\pi_{x,t}^A\right)$, exchange rate rer_t, and interest rate r_t.

Real output growth is supposed to respond contemporaneously and with lags to weather variations. Foreign output growth, agricultural output growth, real exchange rate, and the weather variable also appear in the lagged relationships. Prices respond to contemporaneous movements of foreign prices. We set a zero restriction on contemporaneous effects weather variations on prices to reflect the idea that prices will only react with a lag following a climatic shock. However, we allow prices to contemporaneously react to variations of exchange rate.

6.1.4 Estimation and Identification Issues

The order condition given by Rothenberg (1971) is a necessary condition for the structural VAR to be identified. The model from eq. (C.56) has $n = 10$ endogenous variables and hence requires $n \times (n-1)/2 = 45$ restrictions. We impose 68 zero restrictions on the contemporaneous matrix (A) and each of the lag-restriction matrices B_l contains 55 zero restrictions. The model we estimate is therefore overidentified. Using the same procedure as in Rohe and Hartermann (2015), we ensure that the rank condition for overidentified models (Rubio-Ramirez et al., 2010) is satisfied.

Model given in eq. (C.56) is estimated as in Rohe and Hartermann (2015)[19] with Bayesian techniques. Priors are set to reflect the idea of Litterman (1986) that each of the time series follows a random walk.

In a nutshell, for the ith structural equation, $1 \leq i \leq n$, the prior is formed following Sims and Zha (1998) and Waggoner and Zha (2003). Denoting a_i and f_i the ith row of the contemporaneous-coefficient matrix A and the ith row of the lagged-coefficient matrix B, respectively, the general form of the prior is given by:

$$\begin{cases} a_i \sim \mathcal{N}(0, \bar{S}_i) \\ f_i \mid a_i \sim \mathcal{N}(\bar{P}_i a_i, \bar{H}_i) \end{cases} . \tag{C.57}$$

The prior covariance matrix of the contemporaneous parameters is specified as a $n \times n$ diagonal matrix whose diagonal elements are given as:

$$\hat{S}_i = \text{diag}\left(\left[\left(\frac{\lambda_0}{\sigma_1}\right)^2 \quad \cdots \quad \left(\frac{\lambda_0}{\sigma_n}\right)^2\right]\right). \tag{C.58}$$

The prior covariance matrix of the parameters in $f_i \mid a_i$ is also a $(np + j) \times (np + j)$ diagonal matrix such that:

$$\bar{H}_i = \text{diag}\left(\left[\left(\frac{\lambda_0\lambda_1}{1^{\lambda_3}\sigma_1}\right)^2 \quad \cdots \quad \left(\frac{\lambda_0\lambda_1}{1^{\lambda_3}\sigma_n}\right)^2 \quad \left(\frac{\lambda_0\lambda_1}{2^{\lambda_3}\sigma_1}\right)^2 \quad \cdots \quad \left(\frac{\lambda_0\lambda_1}{p^{\lambda_3}\sigma_1}\right)^2 \quad \lambda_4 \quad \cdots \quad \lambda_j\right]\right). \tag{C.59}$$

The prior means of contemporaneous parameters are supposed to be null, while the prior means of lagged parameters incorporate the random walk assumption by setting $\bar{P}_i$ such that:

$$\bar{P}_i = \begin{bmatrix} I \\ 0 \end{bmatrix}. \tag{C.60}$$

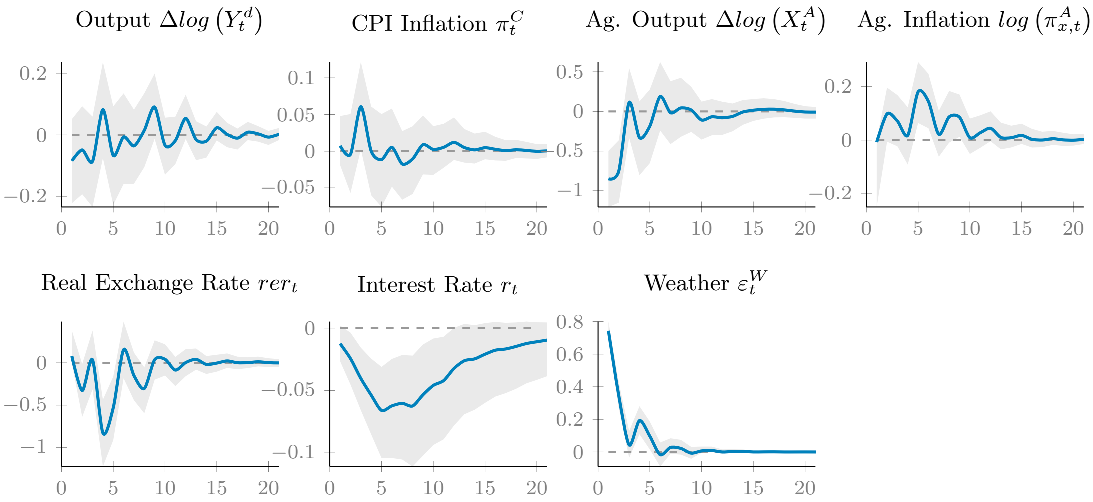
Prior information in the Bayesian estimation is weighted according to the values selected for the hyperparameters of eq. (C.58) and eq. (C.59).[20]

[19] We thank Matthias Hartermann for the R code he provided.

[20] We follow Rohe and Hartermann (2015), Sims and Zha (1998) and Bhuiyan (2012) in the choice of the values given to the hyperparameters: $\lambda_0 = 1$, $\lambda_1 = 0.5$, $\lambda_3 = 0.1$ and $\lambda_4 = \cdots = \lambda_j = \lambda_0 \times \lambda_4 = 1$, with $\lambda_4 = 1$.

6.2 Macroeconomic Response to Weather Shocks

We now present the empirical results of the impulse responses to a one standard deviation shock to the weather variable *i.e.*, the drought indicator to assess the macroeconomic response following this shock.[21] These IRFs are reported in fig. C.4. The solid lines are the responses while the grey areas are the eighty-four percent confidence bands obtained from $20,000$ iterations of the Gibbs sampler and $5,000$ more iterations for the burn-in. The responses are computed for 20 periods.

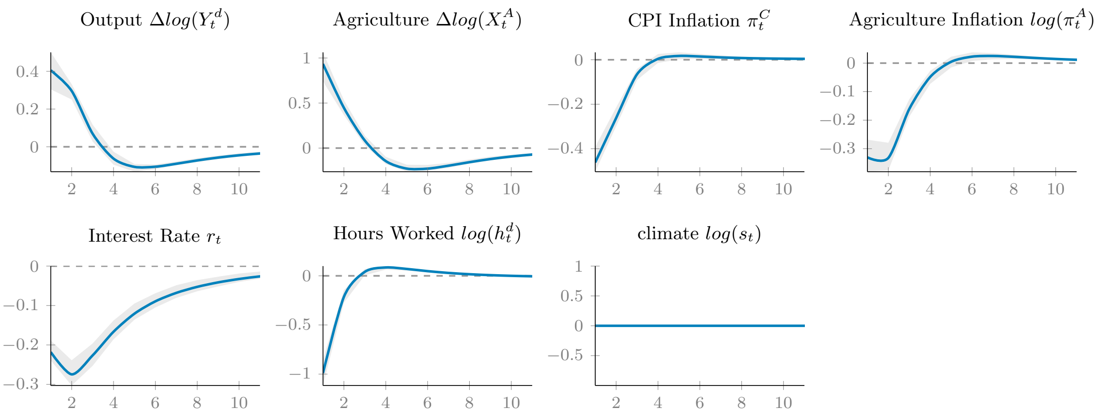


Notes: The blue line is the median of the distribution of the IRFs generated when parameters are drawn from the posterior distribution. The grey areas represent the 16th and 84th percentiles from the draws. The response horizon is in quarters.

Figure C.4: Impulse Responses of the VAR Model due to Weather Shock

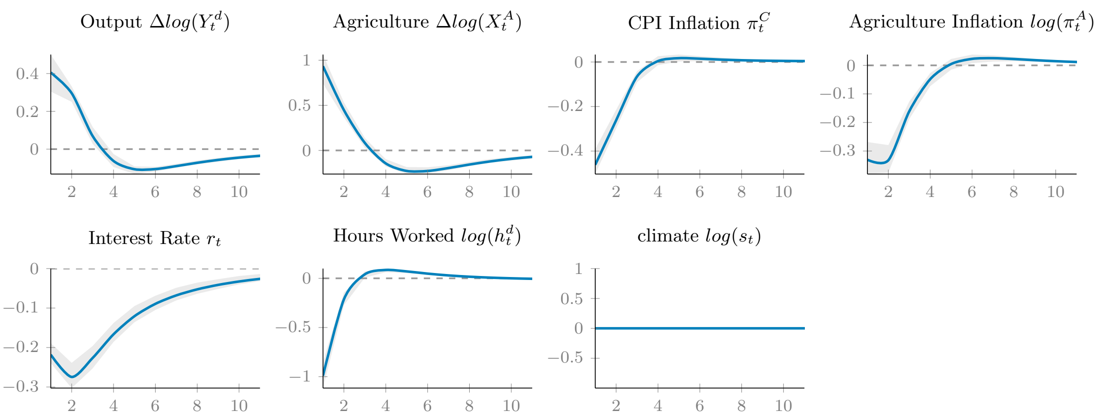
Figure C.4 shows multiple channels affecting the business cycles after a climate shock. In line with (Buckle et al., 2007), domestic output immediately falls. The fall in the agricultural output is also instantaneous, and for the agricultural output, the effects remain until four quarters before they become insignificant. In reaction to the GDP decline, the central bank decreases the interest rate. Agricultural production prices eventually rise in reaction to the adverse supply shock. This expansion may be due to the rise in costs sustained by farmers. To offset the adverse effects of a drought, farmers may use more inputs, such as water that is needed to feed livestock or irrigate cultures. The exchange rate initially appreciates following the climate shock, as specified in the model, but eventually depreciates before it reverts back to trend after two years and a half. The agricultural sector represents a substantial portion of New Zealand's exports, so the decline in agricultural output may lead to a decline in exports followed by a depreciation of the exchange rate.

[21] We focus on the shock to the weather variable. The complete set of IRFs is available upon request.



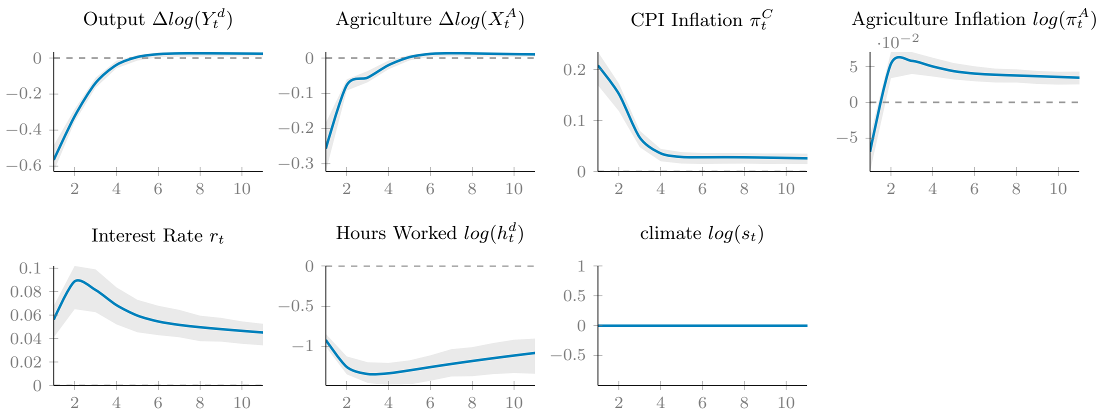
NOTE: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

FIGURE C.5: IRF to an Estimated Productivity Shock η_t^Z Affecting Both Sectors



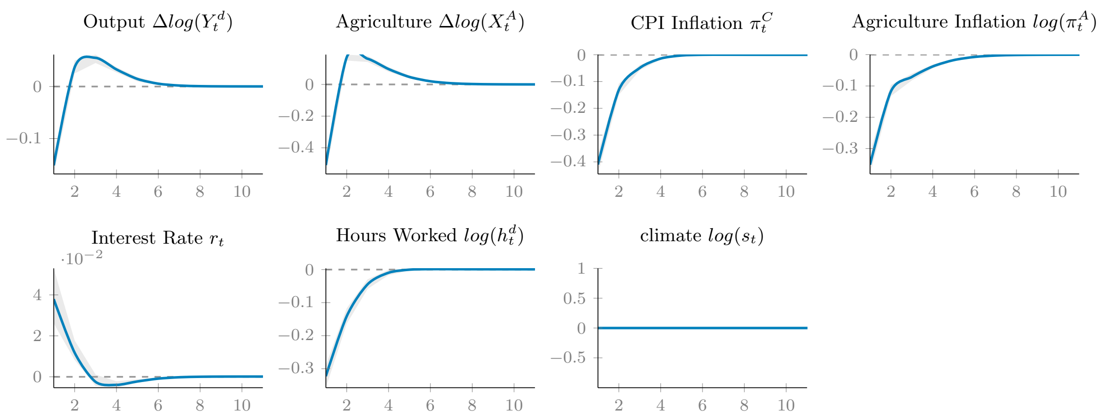
NOTE: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

FIGURE C.6: IRF to a Preference Shock η_t^D affecting the Consumption Index of Households



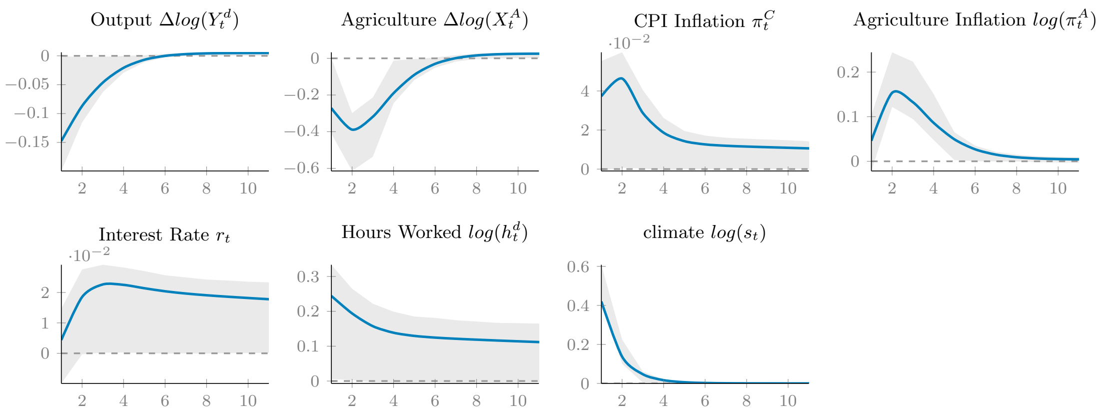
Note: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

Figure C.7: IRF to a Markup Shock η_t^N Affecting Prices of Non-agricultural Goods



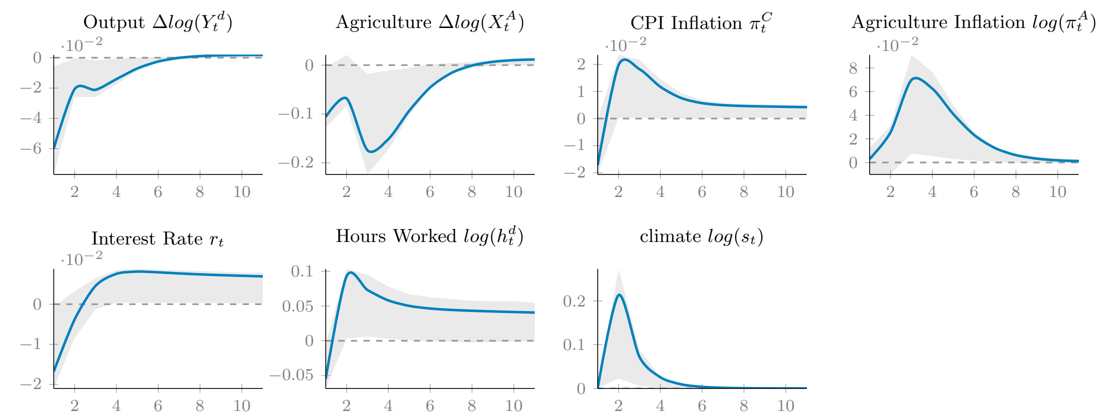
Note: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

Figure C.8: IRF to a Monetary Policy Shock η_t^R



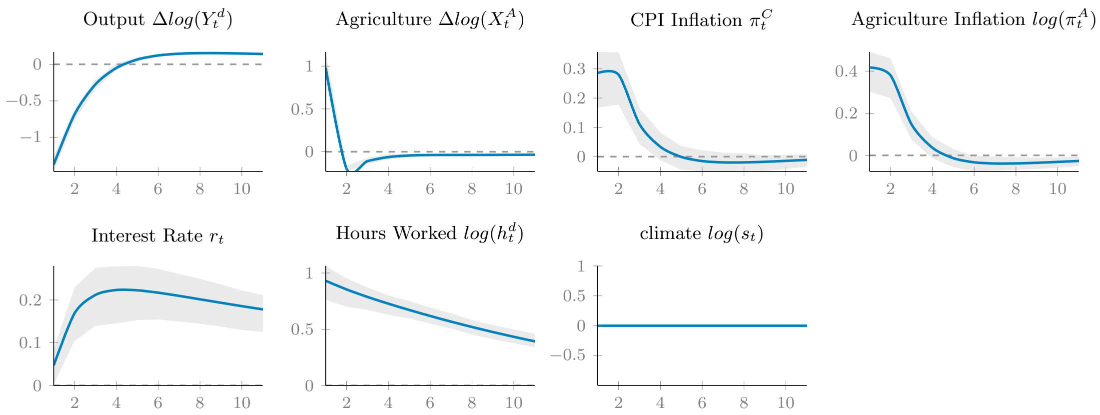
Note: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

Figure C.9: IRF to a Weather Surprise Shock η_t^S



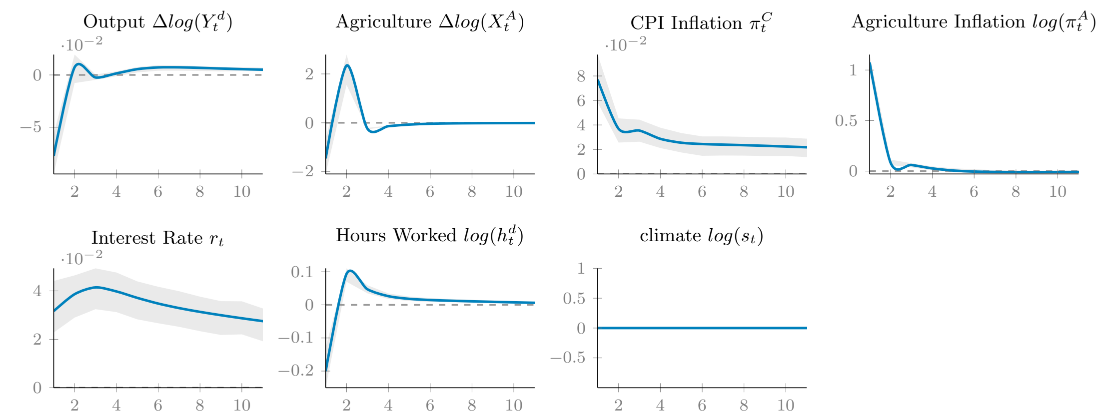
Note: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

Figure C.10: IRF to a Weather-news Shock $\hat{\eta}_{t-1}^S$ (Expected one Quarter in Advance)



NOTE: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

FIGURE C.11: IRF to a Foreign Demand Shock η_t^{*Y}



NOTE: Colored lines are the posterior means, grey areas are the 90 percent HPD intervals. IRF are reported as percentage deviations from the deterministic steady state.

FIGURE C.12: IRF to a Foreign Agricultural Price Shock η_t^{*A}

List of Figures

List of Tables

Bibliography

Adams, R., Hurd, B., Lenhart, S., and Leary, N. (1998). Effects of global climate change on agriculture: an interpretative review. *Climate Research*, 11(1):19–30.

Adams, R. M., Rosenzweig, C., Peart, R. M., Ritchie, J. T., McCarl, B. A., Glyer, J. D., Curry, R. B., Jones, J. W., Boote, K. J., and Allen, L. H. (1990). Global climate change and US agriculture. *Nature*, 345(6272):219–224.

Adjemian, S., Bastani, H., Juillard, M., Mihoubi, F., Perendia, G., Ratto, M., and Villemot, S. (2011). Dynare: Reference manual, version 4. *Dynare Working Papers*, 1.

Aggarwal, P. K. and Mall, R. (2002). Climate change and rice yields in diverse agro-environments of India. II. effect of uncertainties in scenarios and crop models on impact assessment. *Climatic Change*, 52(3):331–343.

Angrist, J. D. and Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *The Journal of Economic Perspectives*, 15(4):69–85.

Annicchiarico, B. and Di Dio, F. (2015). Environmental policy and macroeconomic dynamics in a new Keynesian model. *Journal of Environmental Economics and Management*, 69:1–21.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2):181–198.

Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.

Barnwal, P. and Kotani, K. (2013). Climatic impacts across agricultural crop yield distributions: An application of quantile regression on rice crops in Andhra Pradesh, India. *Ecological Economics*, 87(0):95 – 109.

Barsky, R. B. and Sims, E. R. (2011). News shocks and business cycles. *Journal of monetary Economics*, 58(3):273–289.

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., et al. (2014). How do various maize crop models vary in their responses to climate change factors? *Global change biology*, 20(7):2301–2320.

Batjes, N., Dijkshoorn, K., van Engelen, V., Fischer, G., Jones, A., Montanarella, L., Petri, M., Prieler, S., Teixeira, E., Wiberg, D., and Shi, X. (2008). Harmonized world soil database (version 1.2).

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *The American economic review*, 96(4):1293–1307.

Berg, E. J. (1961). Backward-sloping labor supply functions in dual economies—the Africa case. *The Quarterly Journal of Economics*, 75(3):468–492.

Bhuiyan, R. (2012). Monetary transmission mechanisms in a small open economy: a Bayesian structural VAR approach. *Canadian Journal of Economics/Revue canadienne d'économique*, 45(3):1037–1061.

Black, R., Bennett, S. R., Thomas, S. M., and Beddington, J. R. (2011). Climate change: Migration as adaptation. *Nature*, 478(7370):447–449.

Blasing, T. (2009). Recent greenhouse gas concentrations.

Bloor, C. and Matheson, T. (2010). Analysing shock transmission in a data-rich environment: a large BVAR for New Zealand. *Empirical Economics*, 39(2):537–558.

Boer, E. (2001). Kriging and thin plate splines for mapping climate variables. *International Journal of Applied Earth Observation and Geoinformation*, 3(2):146–154.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M. H., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., et al. (1998). STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. *Agronomie*, 18(5-6):311–346.

Brooks, S. P. and Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of computational and graphical statistics*, 7(4):434–455.

Bruinsma, J. (2009). The resource outlook to 2050. In *Expert meeting on how to feed the world in*, volume 2050, pages 1–33.

Buckle, R. A., Kim, K., Kirkham, H., McLellan, N., and Sharma, J. (2007). A structural VAR business cycle model for a volatile small open economy. *Economic Modelling*, 24(6):990–1017.

Butt, T. A., McCarl, B. A., Angerer, J., Dyke, P. T., and Stuth, J. W. (2005). The economic and food security implications of climate change in Mali. *Climatic change*, 68(3):355–378.

Cabas, J., Weersink, A., and Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic Change*, 101(3-4):599–616.

Castagnini, R., Menon, M., and Perali, F. (2004). Extended and full incomes at the household and individual level: an application to farm households. *American Journal of Agricultural Economics*, 86(3):730–736.

Chaturvedi, R. K., Joshi, J., Jayaraman, M., Bala, G., and Ravindranath, N. (2012). Multi-model climate change projections for India under representative concentration pathways. *Current Science*, 103(7):791–802.

Chen, C.-C., McCarl, B. A., and Schimmelpfennig, D. E. (2004). Yield variability as influenced by climate: a statistical investigation. *Climatic Change*, 66(1-2):239–261.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of political Economy*, 113(1):1–45.

Chung, U., Gbegbelegbe, S., Shiferaw, B., Robertson, R., Yun, J. I., Tesfaye, K., Hoogenboom, G., and Sonder, K. (2014). Modeling the effect of a heat wave on maize production in the USA and its implications on food security in the developing world. *Weather and Climate Extremes*, 5:67–77.

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogée, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., et al. (2005). Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature*, 437(7058):529–533.

Clarida, R., Galí, J., and Gertler, M. (1998). Monetary policy rules in practice: some international evidence. *european economic review*, 42(6):1033–1067.

Cline, W. R. (1996). The impact of global warming of agriculture: comment. *The American Economic Review*, 86(5):1309–1311.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W., Johns, T., Krinner, G., et al. (2013). Long-term climate change: projections, commitments and irreversibility.

Cubasch, U., Wuebbles, D., Chen, D., Facchini, M., Frame, D., Mahowald, N., and Winther, J. (2013). Climate change 2013: the physical science basis. *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge, United Kingdom and New York, NY, USA*, pages 119–158.

Cushman, D. O. and Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary economics*, 39(3):433–448.

Dasgupta, P. and Goldar, B. (2006). Female labour supply in rural India: An econometric analysis. *Indian Journal of Labour Economics*, 49(2):293–310.

De Janvry, A., Fafchamps, M., and Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. *The Economic Journal*, 101(409):1400–1417.

De Salvo, M., Raffaelli, R., and Moser, R. (2013). The impact of climate change on permanent crops in an Alpine region: A Ricardian analysis. *Agricultural Systems*, 118(0):23 – 32.

Deaton, A. (1997). *The analysis of household surveys: a microeconometric approach to development policy*. World Bank Publications.

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system. *The American economic review*, 70(3):312–326.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature*, 52(3):740–798.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19(2):248–255.

Desai, S., Dubey, A., Joshi, B., Sen, M., Shariff, A., and Vanneman, R. (2005). India human development survey (IHDS). *University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi.*

Desai, S. and Vanneman, R. (2016). India human development survey-II (IHDS-II), 2011-12. *University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi.*

Desai, S. B., Dubey, A., Joshi, B. L., Sen, M., Shariff, A., and Vanneman, R. (2010). *Human Development in India.* Oxford University, New York.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *The American Economic Review*, 97(1):354–385.

Deschenes, O. and Kolstad, C. (2011). Economic impacts of climate change on California agriculture. *Climatic Change*, 109(1):365–386.

Dessing, M. (2002). Labor supply, the family and poverty: the S-shaped labor supply curve. *Journal of Economic Behavior & Organization*, 49(4):433–458.

Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3):829–846.

Dinar, A. and Mendelsohn, R. O. (2011). *Handbook on climate change and agriculture.* Edward Elgar Publishing.

Dissou, Y. and Karnizova, L. (2016). Emissions cap or emissions tax? A multi-sector business cycle analysis. *Journal of Environmental Economics and Management.*

Dixit, A. K. and Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *The American Economic Review*, 67(3):297–308.

Easterling, W. E., Aggarwal, P. K., Batima, P., Brander, K. M., Erda, L., Howden, S. M., Kirilenko, A., Morton, J., Soussana, J.-F., Schmidhuber, J., et al. (2007). Food, fibre and forest products. In Parry, M., Canziani, O. F., Palutikof, J. P., van der Linden, P. J., Hanson, C. E., et al., editors, *Climate Change 2014, Mitigation of Climate Change.*, chapter 5, pages 273–313. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., Stechow, C. v., Zwickel, T., and Minx, J. (2014). IPCC, 2014: Summary for policymakers. In of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, C., editor, *Climate Change 2014, Mitigation of Climate Change.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Fankhauser, S. and Tol, R. S. (2005). On climate change and economic growth. *Resource and Energy Economics*, 27(1):1–17.

FAO (2017). Crop prospects and food situation. Technical report, Food and Agriculture Organization of the United Nations, Rome.

Field, C. B., Jackson, R. B., and Mooney, H. A. (1995). Stomatal responses to increased CO2: implications from the plant to the global scale. *Plant, Cell & Environment*, 18(10):1214–1225.

Fischer, C. and Springborn, M. (2011). Emissions targets and the real business cycle: Intensity targets versus caps or taxes. *Journal of Environmental Economics and Management*, 62(3):352–366.

Fischer, G., Shah, M., Tubiello, F. N., and Van Velhuizen, H. (2005). Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1463):2067–2083.

Fisher, A. C., Hanemann, W. M., Roberts, M. J., and Schlenker, W. (2012). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *The American Economic Review*, 102(7):3749–3760.

Fleischer, A., Lichtman, I., and Mendelsohn, R. (2008). Climate change, irrigation, and Israeli agriculture: Will warming be harmful? *Ecological economics*, 65(3):508–515.

Füssel, H.-M., Jol, A., et al. (2012). Climate change, impacts and vulnerability in Europe 2012 an indicator-based report. Technical report, Luxembourg: Publications Office of the European Union.

Galí, J. and Monacelli, T. (2005). Monetary policy and exchange rate volatility in a small open economy. *The Review of Economic Studies*, 72(3):707–734.

García, M. and Viladrich, M. (2009). The economic relevance of climate variables in agriculture: The case of Spain. *Economía agraria y recursos naturales*, 9(2):149–180.

García-Herrera, R., Díaz, J., Trigo, R., Luterbacher, J., and Fischer, E. (2010). A review of the European summer heat wave of 2003. *Critical Reviews in Environmental Science and Technology*, 40(4):267–306.

Gbetibouo, G. and Hassan, R. (2005). Measuring the economic impact of climate change on major South African field crops: a Ricardian approach. *Global and Planetary Change*, 47(2-4):143 – 152.

Geweke, J. (1999). Using simulation methods for Bayesian econometric models: inference, development, and communication. *Econometric reviews*, 18(1):1–73.

Greenwood, J., Hercowitz, Z., and Huffman, G. W. (1988). Investment, capacity utilization, and the real business cycle. *The American Economic Review*, pages 402–417.

Haim, D., Shechter, M., and Berliner, P. (2008). Assessing the impact of climate change on representative field crops in Israeli agriculture: a case study of wheat and cotton. *Climatic Change*, 86(3-4):425–440.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1):153–161.

Henning, C. H. and Henningsen, A. (2007). Modeling farm households' price responses in the presence of transaction costs and heterogeneity in labor markets. *American Journal of Agricultural Economics*, 89(3):665–681.

Henningsen, A. (2014). *micEconAids: Demand Analysis with the Almost Ideal Demand System (AIDS)*. R package version 0.6-16.

Heutel, G. (2012). How should environmental policy respond to business cycles? Optimal policy under persistent productivity shocks. *Review of Economic Dynamics*, 15(2):244–264.

Hope, C., Anderson, J., and Wenman, P. (1993). Policy analysis of the greenhouse effect: an application of the PAGE model. *Energy Policy*, 21(3):327–338.

Howard, P., Sterner, T., et al. (2014). Raising the temperature on food prices: Climate change, food security, and the social cost of carbon.

Hutchinson, M. (1995). Interpolating mean rainfall using thin plate smoothing splines. *International journal of geographical information systems*, 9(4):385–403.

Iacoviello, M. and Neri, S. (2010). Housing market spillovers: evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics*, 2(2):125–164.

Jacoby, H. G. (1993). Shadow wages and peasant family labour supply: an econometric application to the Peruvian Sierra. *The Review of Economic Studies*, 60(4):903–921.

Jones, C. A., Kiniry, J. R., and Dyke, P. (1986). *CERES-Maize: A simulation model of maize growth and development.* Texas A& M University Press.

Jones, P. G. and Thornton, P. K. (2003). The potential impacts of climate change on maize production in Africa and Latin America in 2055. *Global environmental change*, 13(1):51–59.

Just, R. E. and Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1):67–86.

Just, R. E. and Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, 61(2):276–284.

Kamber, G., McDonald, C., Price, G., et al. (2013). Drying out: Investigating the economic effects of drought in New Zealand. Technical report, Reserve Bank of New Zealand Analytical Note Series No. AN2013/02, Reserve Bank of New Zealand, Wellington, New Zealand.

Khanal, A. R., Mishra, A. K., and Bhattarai, M. (2014). Weather risk and cropping intensity: A non-stationary and dynamic panel modeling approach. In *2014 Annual Meeting, July 27-29, 2014, Minneapolis, Minnesota*, number 170603. Agricultural and Applied Economics Association.

Kim, M.-K., Pang, A., et al. (2009). Climate change impact on rice yield and production risk. *Journal of Rural Development*, 32(2):17–29.

Kim, S. and Roubini, N. (2000). Exchange rate anomalies in the industrial countries: A solution with a structural VAR approach. *Journal of Monetary Economics*, 45(3):561–586.

Koenker, R. (2005). *Quantile regression.* Number 38. Cambridge university press.

Koenker, R. and Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, pages 33–50.

Kumar, K. and Parikh, J. (1998). Climate change impacts on Indian agriculture: the Ricardian approach. In Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J., and Lonergan, S., editors, *Measuring the impact of climate* *change on Indian agriculture*, pages 141–184. World Bank Technical Paper No. 402, World Bank, Washington, DC.

Kumar, K. and Parikh, J. (2001). Indian agriculture and climate sensitivity. *Global environmental change*, 11(2):147–154.

Kumar, K. K. (2011). Climate sensitivity of Indian agriculture: do spatial effects matter? *Cambridge Journal of Regions, Economy and Society*, 4(2):221–235.

Kurukulasuriya, P. and Mendelsohn, R. (2008). A Ricardian analysis of the impact of climate change on African cropland. *African Journal Agriculture and Resource Economics*, 2(1):1–23.

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H. M., Fosu, K. Y., Gbetibouo, G., Jain, S., et al. (2006). Will African agriculture survive climate change? *The World Bank Economic Review*, 20(3):367–388.

Lang, G. (2007). Where are Germany's gains from Kyoto? Estimating the effects of global warming on agriculture. *Climatic Change*, 84(3-4):423–439.

Lippert, C., Krimly, T., and Aurbacher, J. (2009). A Ricardian analysis of the impact of climate change on agriculture in Germany. *Climatic Change*, 97(3-4):593–610.

Litterman, R. B. (1986). Forecasting with Bayesian vector autoregressions?five years of experience. *Journal of Business & Economic Statistics*, 4(1):25–38.

Liu, P. (2006). A small new Keynesian model of the New Zealand economy. *Reserve Bank of New Zealand*, 3.

Lobell, D. B. and Asner, G. P. (2003). Climate and management contributions to recent trends in US agricultural yields. *Science*, 299(5609):1032–1032.

Lobell, D. B. and Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology*, 150(11):1443–1452.

Lobell, D. B. and Field, C. B. (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental research letters*, 2(1):014002.

Lobell, D. B. and Ortiz-Monasterio, J. I. (2007). Impacts of day versus night temperatures on spring wheat yields. *Agronomy journal*, 99(2):469–477.

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042):616–620.

Maddison, D. (2000). A hedonic analysis of agricultural land prices in England and Wales. *European Review of Agricultural Economics*, 27(4):519–532.

McCarl, B. A., Villavicencio, X., and Wu, X. (2008). Climate change and future analysis: is stationarity dying? *American Journal of Agricultural Economics*, 90(5):1241–1247.

McLean, R., Sinha, S., Mirza, M., and Lal, M. (1998). Tropical Asia. In Watson, R. T., Zinyowera, M. C., and Moss, R. H., editors, *The regional impact of climate change: an assessment of vulnerability*, pages 381–407. Cambridge University Press.

Mearns, L. O., Rosenzweig, C., and Goldberg, R. (1997). Mean and variance change in climate scenarios: methods, agricultural applications, and measures of uncertainty. *Climatic Change*, 35(4):367–396.

Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, 1(1):5–19.

Mendelsohn, R., Basist, A., Kurukulasuriya, P., and Dinar, A. (2007). Climate and rural income. *Climatic Change*, 81(1):101–118.

Mendelsohn, R., Dinar, A., and Sanghi, A. (2001). The effect of development on the climate sensitivity of agriculture. *Environment and Development Economics*, 6:85–101.

Mendelsohn, R., Dinar, A., and Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and Development Economics*, 11(02):159–178.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture: A Ricardian analysis. *American Economic Review*, 84(4):753–71.

Mendelsohn, R. O. and Dinar, A. (2009). *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects.* Edward Elgar Publishing.

Miao, R., Khanna, M., and Huang, H. (2015). Responsiveness of crop yield and acreage to prices and climate. *American Journal of Agricultural Economics*, 98(1):191–211.

Mitra, A., Kumar, M. D., Kumar, K. R., Abrol, Y., Kalra, N., Velayutham, M., and Naqvi, S. (2002). Global change and biogeochemical cycles: the South Asia region. In *Global-Regional linkages in the earth system*, pages 75–107. Springer.

Mundlak, Y. (2001). Production and supply. *Handbook of agricultural economics*, 1:3–85.

Narasimhan, B. and Srinivasan, R. (2005). Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology*, 133(1):69–88.

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The economic journal*, 101(407):920–937.

Nordhaus, W. D. (1994). *Managing the global commons: the economics of climate change*, volume 31. MIT press Cambridge, MA.

Nordhaus, W. D. (2007). A review of the Stern review on the economics of climate change. *Journal of economic literature*, 45(3):686–702.

Nordhaus, W. D. and Yang, Z. (1996). A regional dynamic general-equilibrium model of alternative climate-change strategies. *The American Economic Review*, pages 741–765.

Nychka, D., Furrer, R., and Sain, S. (2015). *fields: Tools for Spatial Data.* R package version 8.2-1.

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., Nygaard, L., et al. (2004). Mapping vulnerability to multiple stressors: climate change and globalization in India. *Global environmental change*, 14(4):303–313.

OECD (2015). The economic consequences of climate change. Technical report.

Parry, M. L., Rosenzweig, C., Iglesias, A., Livermore, M., and Fischer, G. (2004). Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global Environmental Change*, 14(1):53–67.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature*, 51(3):860–872.

Polsky, C. (2004). Putting space and time in Ricardian climate change impact studies: Agriculture in the US Great Plains, 1969–1992. *Annals of the Association of American Geographers*, 94(3):549–564.

Polsky, C. and Easterling III, W. E. (2001). Adaptation to climate variability and change in the US Great Plains: A multi-scale analysis of Ricardian climate sensitivities. *Agriculture, Ecosystems & Environment*, 85(1):133–144.

Quiggin, J. and Horowitz, J. K. (1999). The impact of global warming on agriculture: a Ricardian analysis: comment. *The American Economic Review*, 89(4):1044.

Rabanal, P. (2007). Does inflation increase after a monetary policy tightening? Answers based on an estimated DSGE model. *Journal of Economic Dynamics and Control*, 31(3):906–937.

Rabanal, P. and Tuesta, V. (2010). Euro-dollar real exchange rate dynamics in an estimated two-country model: an assessment. *Journal of Economic Dynamics and Control*, 34(4):780–797.

Restuccia, D., Yang, D. T., and Zhu, X. (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics*, 55(2):234–250.

Ritchie, J. and Otter, S. (1985). Description and performance of CERES-Wheat: a user-oriented wheat yield model. *ARS-United States Department of Agriculture, Agricultural Research Service (USA).*

Rohe, C. and Hartermann, M. (2015). The role of external shocks for monetary policy in Colombia and Brazil: A Bayesian SVAR analysis. Technical report, Center for Quantitative Economics (CQE), University of Muenster.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., et al. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences*, 111(9):3268–3273.

Rosenzweig, C. and Parry, M. L. (1994). Potential impact of climate change on world food supply. *Nature*, 367(6459):133–138.

Rotemberg, J. J. (1982). Monopolistic price adjustment and aggregate output. *The Review of Economic Studies*, 49(4):517–531.

Rothenberg, T. J. (1971). Identification in parametric models. *Econometrica: Journal of the Econometric Society*, pages 577–591.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Rupa Kumar, K., Krishna Kumar, K., Ashrit, R., Patwardhan, S., and Pant, G. (2002). Climate change in India: Observations and model projections. *Climate Change and India: IIssues, Concerns and Opportunities. Tata McGraw-Hill Publishing Company Limited, New Delhi.*

Sadoulet, E., De Janvry, A., and Benjamin, C. (1998). Household behavior with imperfect labor markets. *Industrial Relations: A Journal of Economy and Society*, 37(1):85–108.

Saha, A., Havenner, A., and Talpaz, H. (1997). Stochastic production function estimation: small sample properties of ML versus FGLS. *Applied Economics*, 29(4):459–469.

Sanghi, A. and Mendelsohn, R. (2008). The impacts of global warming on farmers in Brazil and India. *Global Environmental Change*, 18(4):655–665.

Sanghi, A., Mendelsohn, R., and Dinar, A. (1998). The climate sensitivity of Indian agriculture. In Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J., and Lonergan, S., editors, *Measuring the impact of climate change on Indian agriculture*, pages 69–139. World Bank Technical Paper No. 402, World Bank, Washington, DC.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *The American Economic Review*, 95(1):395–406.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. *The Review of Economics and Statistics*, 88(1):113–125.

Schlenker, W. and Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, 5(1):014010.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Schmidhuber, J. and Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104(50):19703–19708.

Schmitt-Grohé, S. and Uribe, M. (2003). Closing small open economy models. *Journal of international Economics*, 61(1):163–185.

Schmitt-Grohé, S. and Uribe, M. (2012). What's news in business cycles. *Econometrica*, 80(6):2733–2764.

Sheehy, J. E., Mitchell, P. L., and Ferrer, A. B. (2006). Decline in rice grain yields with temperature: models and correlations can give different estimates. *Field Crops Research*, 98(2):151–156.

Sicular, T. and Zhao, Y. (2004). *China and the WTO: accession, policy reform, and poverty reduction strategies*, chapter Earnings and Labor Mobility in Rural China: Implications for China's Accession to the WTO. World Bank Publications.

Sims, C. A. and Zha, T. (1998). Bayesian methods for dynamic multivariate models. *International Economic Review*, pages 949–968.

Singh, I., Squire, L., and Strauss, J. (1986). *Agricultural household models: Extensions, applications, and policy*. The World Bank.

Skoufias, E. (1994). Using shadow wages to estimate labor supply of agricultural households. *American Journal of Agricultural Economics*, 76(2):215–227.

Smets, F. and Wouters, R. (2003). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European Economic Association*, 1(5):1123–1175.

Smets, F. and Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review*, 97(3):586–606.

Srinivasan, P. and Jha, S. (2001). Liberalized trade and domestic price stability. the case of rice and wheat in India. *Journal of Development Economics*, 65(2):417–441.

Stern, N. H. (2007). *The economics of climate change: the Stern review*. cambridge University press.

Swain, A. K. (2014). Can India reform its agriculture? | the diplomat.

Taylor, J. E. and Adelman, I. (2003). Agricultural household models: genesis, evolution, and extensions. *Review of Economics of the Household*, 1(1-2):33–58.

Tilman, D., Balzer, C., Hill, J., and Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, 108(50):20260–20264.

Tol, R. S. (1995). The damage costs of climate change toward more comprehensive calculations. *Environmental and Resource Economics*, 5(4):353–374.

Tol, R. S. (2002). Estimates of the damage costs of climate change. Part 1: Benchmark estimates. *Environmental and resource Economics*, 21(1):47–73.

Tol, R. S. (2005). The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. *Energy policy*, 33(16):2064–2074.

Tol, R. S. (2009). The economic effects of climate change. *The Journal of Economic Perspectives*, pages 29–51.

Tubiello, F. N. and Fischer, G. (2007). Reducing climate change impacts on agriculture: Global and regional effects of mitigation, 2000–2080. *Technological Forecasting and Social Change*, 74(7):1030–1056.

Van Passel, S., Massetti, E., and Mendelsohn, R. (2016). A Ricardian analysis of the impact of climate change on European agriculture. *Environmental and Resource Economics*, pages 1–36.

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., et al. (2011). The representative concentration pathways: an overview. *Climatic change*, 109(1-2):5.

Vanschoenwinkel, J., Mendelsohn, R., and Van Passel, S. (2016). Do Western and Eastern Europe have the same agricultural climate response? Taking adaptive capacity into account. *Global Environmental Change*, 41:74–87.

Waggoner, D. F. and Zha, T. (2003). Likelihood preserving normalization in multiple equation models. *Journal of Econometrics*, 114(2):329–347.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., and Zhang, L. (2009). The impact of climate change on China's agriculture. *Agricultural Economics*, 40(3):323–337.

Weitzman, M. L. (2010). What is the" damages function" for global warming—and what difference might it make? *Climate Change Economics*, 1(01):57–69.

Xiong, W., Declan, C., Erda, L., Yinlong, X., Hui, J., Jinhe, J., Ian, H., and Yan, L. (2009). Future cereal production in China: the interaction of climate change, water availability and socio-economic scenarios. *Global Environmental Change*, 19(1):34–44.

You, L., Rosegrant, M. W., Wood, S., and Sun, D. (2009). Impact of growing season temperature on wheat productivity in China. *Agricultural and Forest Meteorology*, 149(6):1009–1014.

VU :
Le Directeur de Thèse
(Nom et Prénom)

VU :
Le Responsable de l'École Doctorale

VU pour autorisation de soutenance

Rennes, le

Le Président de l'Université de Rennes 1

David ALIS

VU après soutenance pour autorisation de publication :

Le Président de Jury,
(Nom et Prénom)

Changement climatique et agriculture

Le climat de la planète se réchauffe et ses effets sont entachés d'une forte incertitude. Une hausse de la température et de la fréquence d'événements extrêmes tels des inondations ou des sécheresses est prévue. La forte dépendance de l'agriculture aux conditions climatiques en fait *de facto* un champ d'application privilégié. Cette thèse se destine ainsi à étudier la relation entre climat et agriculture, afin d'évaluer les conséquences potentielles du changement climatique, en mêlant travaux empiriques et théoriques. Les deux premiers chapitres se concentrent sur les pays en développement au travers de deux études examinant la production et les profits agricoles ainsi que les décisions de consommation des ménages agricoles indiens. Les divers scénarios climatiques envisagés montrent un effet global négatif sur la production et les profits, particulièrement pour les ménages agricoles du sud du pays. L'irrigation tout comme le mélange des cultures permettent toutefois de réduire les dommages subis, notamment pour les petits exploitants. Les deux chapitres suivants considèrent des pays économiquement développés, en commençant par une étude des rendements céréaliers européens. Les projections sous les différents scénarios climatiques indiquent une faible croissance des rendements du blé d'ici à la fin du XXI^{e} siècle, comparativement aux observations des 25 dernières années. Ces gains faibles sont toutefois accompagnés d'une forte hétérogénéité régionale. Pour le maïs, des faibles gains d'ici la moitié du XXI^{e} s'effacent derrières de plus fortes pertes dans le long terme. L'approche partielle est ensuite délaissée pour laisser place à une analyse en équilibre général s'attachant à étudier les effets de court terme des chocs climatiques sur les cycles économiques, à travers leur impact sur l'agriculture. Une hausse de la variance des chocs climatiques conformément à celle prévue par des scénarios climatiques entraîne un accroissement substantiel de variables macroéconomiques telles la production et l'inflation.

Mots clés : Agriculture, Changement Climatique, Cycles Économiques, Ménages Agricoles, Petite Économie Ouverte, Régression Quantile, Rendements Céréaliers, Système de Demande (AIDS).

Climate Change and Agriculture

Global climate is warming, and the effects of climate change are associated with a lot of uncertainty. Not only average temperatures are expected to rise, but also the occurrence of extreme events such as floods or droughts. Agriculture is particularly at risk, due to the importance of weather conditions in production. This thesis therefore aims at investigating the relationship between weather variations and agricultural production, to better assess the potential effects of climate change on agriculture, relying on both theoretical and empirical methods. The first two chapters focus on developing countries and provide two empirical studies based on Indian data at the individual farm level that link climate to agricultural production and profits and to consumption decisions. We find contrasted results, with an overall damaging effect of climate change scenarios on Indian agricultural production and profits, especially for farmers in southern India. Irrigation may however help mitigating the losses, as well as crop mixing, particularly for small farms. The last two chapters consider developed countries. The first step focuses on crop yields in Europe. Under the tested climate scenarios, wheat yields are projected to slightly increase by the end of the 21st century relative to the observed yields from the past 25 years. These small gains are however accompanied by a lot of regional heterogeneity. For European corn yields, the projections highlight small gains in by the middle of the 21st century, followed by relatively higher losses in the long run. The second step relies on a general equilibrium approach, and aims at investigating the short-run impacts of weather shocks on business cycles, through their damaging effects on agriculture. Increasing the variance of climate shocks in accordance with forthcoming climate change leads to a sizeable increase in the volatility of key macroeconomic variables, such as production and inflation.

Keywords : Agriculture; Business Cycles; Climate Change; Demand System (AIDS); Crop Yields; Household Behaviour; Quantile Regression; Small Open Economy.