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Essays on Regulatory Impact in Electricity and Internet Markets

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Essays on Regulatory Impact in Electricity and Internet Markets

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For Katie, Caleb, and Allison, for all your love, with all my heart.

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Essays on Regulatory Impact in Electricity and Internet Markets

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This dissertation details regulation's impact in networked markets, notably in deregulated electricity and internet service markets. These markets represent basic infrastructure in the modern economy; their innate networked structures make for rich fields of economic research on regulatory impact.

The first chapter models deregulated electricity industries with a focus on the Texas market. Optimal economic benchmarks are considered for markets with regulated delivery and interrelated network costs. Using a model of regulator, consumer, and firm interaction, I determine the efficiency of the current rate formalization compared to Ramsey-Boiteux prices and two-part tariffs. I find within Texas's market increases to generator surplus up to 55% of subsidies could be achieved under Ramsey-Boiteux pricing or two-part tariffs, respectively.

The second chapter presents a framework to analyze dynamic processes and long-run outcomes in two-sided markets, specifically dynamic platform and firm investment incentives within the internet-service platform/content provision market. I use the Ericson-Pakes framework applied within a platform that chooses fees on either side of its two-sided market. This chapter determines the impact of network neutrality on platform investment incentives, specifically whether to improve the platform. I use a parameterized calibration from engineering reports and current ISP literature to determine welfare outcomes and industry behavior under network neutral and non-neutral regimes.

My final chapter explores retail firm failure within the deregulated Texas retail electricity market. This chapter investigates determinants of retail electric firm failures using duration analysis frameworks. In particular, this chapter investigates the impact of these determinants on firms with extant experience versus unsophisticated entrants. Understanding these determinants is an important component in evaluating whether deregulation achieves the impetus of competitive electricity market restructuring. Knowing which economic events decrease a market's competitiveness helps regulators to effectively evaluate policy implementations. I find that experience does benefit a firm's duration, but generally that benefit assists firm duration in an adverse macroeconomic environment rather than in response to adverse market conditions such as higher wholesale prices or increased transmission congestion. Additionally, I find evidence that within the Texas market entering earlier results in a longer likelihood of duration.

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Chapter 1

Optimal Transmission Regulation in Restructured Electricity Markets

1.1 Introduction

Electricity is a fundamental part of the modern economy. Broadly, one can separate electricity supply into three categories: power producers (generators), power deliverers (transmission firms), and retailers (power companies). Recent policy and technical innovations have opened up the generator and retailer functions to entry and competition while keeping the separate transmission portion regulated. This paper investigates the problem of the regulator, which faces a number of tensions when balancing social welfare with firm participation incentives.

To investigate the regulator's problem I examine these fundamental economic tensions and quantify the welfare distortions of the current transmission pricing policy in Texas versus a first-best (two-part tariff) and second-best pricing regime.[1] In regulating transmission firms, regulators use policies that affect wholesale energy market participants, including consumers and generators. Transmission firms are natural monopolies that serve different types

[1]See appendix A for a review of Ramsey pricing.

of consumers. The standard formulation of regulating the prices of a natural monopoly is a Ramsey-Boiteux type model which maximizes social welfare subject to the natural monopoly's budget breaking even. The Ramsey-Boiteux model recommends a departure from marginal cost pricing with prices that are proportional to each consumer type's elasticities of demand; this departure then pays for fixed and variable costs through a per-unit price. My paper builds on this classical framework by incorporating the transmission firm as a regulated fulfiller of the deregulated wholesale market. The current policy of electricity regulation does not follow this theoretically optimal specification, and instead uses a different rule that ignores consumer heterogeneity and demand response. By ignoring these economically significant factors, these current regulatory policies institutionalize misallocations of economic resources by market participants.

My empirical focus is the Texas electricity market, which adopted a separated wholesale market structure in 1999 and deregulated retail market structure in 2002. At 1.22 trillion USD per year the Texas economy is larger than the fifteenth largest national economy; because of this, electricity transmission rates play a major role in production and consumption decisions of downstream manufacturers and residents. The transmission network serving the majority of Texas is functionally an island as it is separate from the rest of the United State's electricity grid. This area, operated by the nonprofit Electric Reliability Council of Texas (ERCOT), is subject primarily to state regulators instead of an amalgamation of state, regional, and federal regulatory authorities. Further, regulation policies in Texas reflect other state public utility commission policies [McDermott, 2012]. These facts make the Texas market a strong candidate for the study of optimal transmission pricing.

The transmission network in Texas is owned by municipalities, rural cooperatives, and investor owned utilities (IOUs). By far the largest players in the network are IOUs; five serve roughly 75%–80% of electric demand in Texas and have their transmission prices set by the Public Utility Commission of Texas (PUCT). Before deregulation of the Texas market, these five networks were vertically integrated in production, transmission, metering, and retail sale of electricity to final consumers. The deregulation of the electricity market specifically refers to dividing these investor-owned vertical monopolies. Legal institutions were implemented to separate the operation of these subsidiaries, and most companies sold off or split their companies [Baldick and Niu, 2005]. What is left is a competitive retail market, wholesale market of generators and retailers, and a fully-regulated transmission firm. The regulatory policy used in transmission pricing for these transmission firms retain a cost-of-service regulation policy.

The historical policy's dead weight loss is large compared to a second-best policy. I find a potential welfare improvement over the current policy of \$8.8 billion (\$9.3 billion before being netted of transmission fixed cost, which may arguably from from alternative sources than from consumer payment. See Coase [1946]). Relative to these first-best policy result, a second-best policy would result in a 74% improvement to dead-weight loss over the current policy, or \$6.8 billion increase to efficiency. The majority of this potential welfare increase is from increases to producer surplus, which, in addition to being of general interest in the regulation literature, is informative for energy, transmission and platform regulatory policy decisions. The US government spent roughly \$13 billion on energy source subsidies in 2006; Texas spent \$1.4 billion; I find that 52% to 56% of this could be covered by increases to producer surplus [Texas Comptroller of Public Accounts, 2008]. These findings imply that Texas subsidies to energy producers could be significantly funded by a shift to a policy that takes into account demand elasticity and wholesale market impacts of transmission pricing.

This paper is related to a literature of economic regulation and utility pricing. The closest project in the nature of this paper is Matsukawa et al. [1993]. In their paper, the authors model a vertically integrated electricity market to quantify the welfare losses the Japanese electricity sector experiences due to deviating from Ramsey-Boiteux pricing. They find that residential consumers' transmission prices are too low and industrial consumer prices too high relative to a Ramsey-Boiteux benchmark. This project also draws many insights from the work of Vogelsang and Finsinger [1979] and Baumol and Bradford [1970] to analyze a regulated natural monopoly subject to Ramsey-Boiteux pricing. The Vogelsang and Finsinger [1979] project derives social welfare maximizing conditions for second-best pricing in a framework of a single regulated monopoly. This paper differs from that framework in that it extends the theory to multiple firms under the same regulator; under this framework the Vogelsang-Finnsinger conclusions do not always hold. Further, the treatment of the regulated firm as a system of delivery underlying a separate market is novel in this literature. Additionally, this paper adds on to insights from recent empirical work in deregulated wholesale electricity markets (Borenstein et al. [2002], Puller [2007], Joskow [2011]) by considering the impact transmission price regulation has on consumer consumption and aggregate market supply.

The analysis and outcomes of this paper add to the literature in three ways. The most obvious is the establishment of an empirical upper bound on welfare gains by switching from the common current regulatory policy to a Ramsey-Boiteux optimum or to a two-part tariff. The second contribution is an analysis of the welfare gainers and losers under current policy in the Texas market. The third is a generalizable empirical framework for regulatory analysis in markets that require a regulated delivery mechanism.

The organization of this paper is as follows: Section 1.2 describes the institutional details regarding general transmission markets and ERCOT-specific details. Section 1.3 describes a model with complete and costless information on the part of the regulator. Section 1.4 describes the data and sources used for estimation. Section 1.5 discusses the econometric strategy and identification of model relevant parameters. Results of the estimation are discussed in section 1.6, followed by conclusions in section 1.7.

1.2 Institutions

In this section I review the regulatory policy and institutions in deregulated electricity markets. First I review general policy followed in the US, and then focus on the specific Texas market institutions from 2002–2010 (a period where the Texas market has a fairly consistent institutional structure as a zonal market).

1.2.1 Transmission in Restructured Electricity Markets

Historically, electricity firms were vertically integrated power producers, deliverers, and retailers. In the 1980s a political push began decoupling these monopolies apart by these functions, which opened portions of the monopoly to efficiency improvements via an open market [Davis and Wolfram, 2012]. Subsequently, in restructured electricity markets the generation, transmission, and occasionally retail functions are decoupled. Generators produce power, and retailers ensures that end-consumer demand is procured. Generators and retailers participate in a wholesale market where energy amounts and delivery date and time are decided. Trade in this market consists of bilateral long-term contracts and spot trading over a platform.[2] Platforms enabling this trade in the US are known as Regional Transmission Operators (RTO) or Independent System Operators (ISO). An RTO operates but does not normally own the electricity transmission network. Instead, one or several firms own

[2]The platform operated in Texas includes a day-ahead futures market and a real-time market that address residual demand/demand shocks.

Operator	**Owner**
Network Expansion Planning	Network Expansion Planning
Manage Scheduled Energy Delivery	Capital Investment
Contracting Ancillary Services	Network Maintenance
Network Access Provision	
Network Reliability (avoid system collapse)	

Table 1.1: Roles of Operator versus Owner

the transmission network. The operator coordinates, monitors, and controls the use of the network. Table 1.1 specifies the primary differences between owning and operating a transmission network. As a general rule, transmission providers are paid for the use of their networks through a regulated rate established by a utility commission. In the US, this is typically done via a linear *cost-of-service* rate (COS) [Joskow, 2011]. COS rates are based on a weighted average of historical fixed and variable costs. Within the industry and in some strands of the regulation literature this average is referred to as the revenue requirement, or rate-of-return regulation [McDermott, 2012]. This cost of service regulation applies to both higher-voltage transmission service as well as lower-tiered distribution service [PUCT, 2013].

1.2.2 The Texas Market

1.2.2.1 Texas Institutional Details

The transmission network in Texas is owned by municipalities, rural cooperatives, and investor-owned utilities (IOUs). By far the largest transmission firms are IOUs, where five serve roughly 75% of electric demand for the network. These five IOUs have their per-unit transmission rates set by the PUCT using a COS regulation policy.

Transmission prices in ERCOT rarely change; the primary transmission charge changed once in the time frame of 2002 until 2010.[3] To address this fact, I use a static model where a regulator chooses a set of linear transmission tariffs without the ability to give transfers directly to the firm. This makes for a more conservative outcome, as the model is based on the current Texas regulation policy design where consumers are charged a per-unit charge for electricity transmission.[4]

ERCOT is the RTO for about 85% of Texas, including many metropolitan areas. Figure 1.1 shows the operating area of ERCOT. ERCOT's operating area covers the majority of the state's metropolitan areas. The process by which ERCOT schedules energy is an important feature of the wholesale market, and hence needs a explanation to understand the model presented in section 1.3. This process begins with generators and retailers committing to bilateral energy delivery contracts; the quantity of these contracts, location of delivery, and time of delivery are given to ERCOT the day before contract maturation. Next, in a day-ahead market, ERCOT accepts offer curves from retailers and generators for excess demand or supply. In practice, a re-

[3]There are *ad hoc* levies applied to the network on short term bases; for example, hurricane damage recovery. However, the primary transmission charge does not typically change, and real transmission fixed and variable costs do not follow a monotonic pattern. According to PUCT substantive rules §25.192, the transmission fee can be updated yearly; this is rare in practice. PUCT [2013]

[4]Per-unit up to a units transformation, established and agreed upon in rate cases.

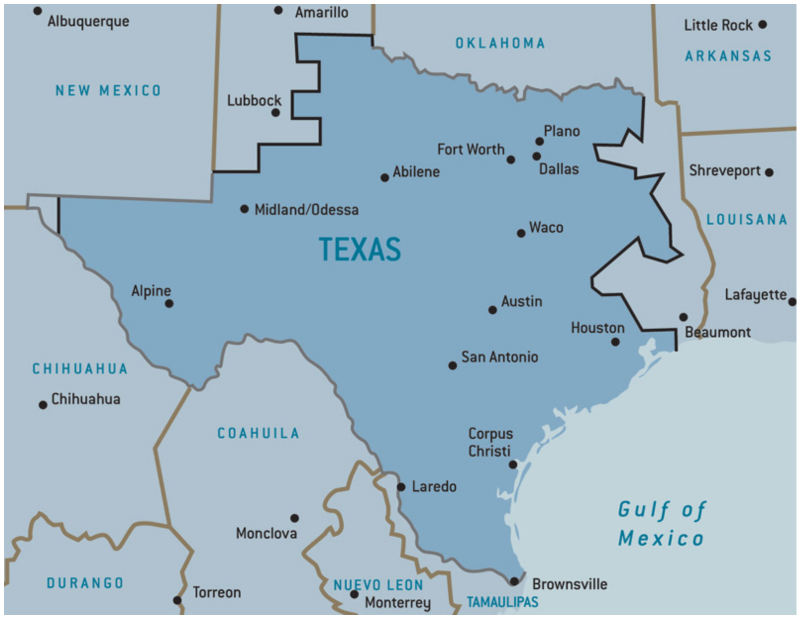

Figure 1.1: Map of ERCOT Region

tailer could purchase all their energy demand or sell excess energy demand in this day-ahead market.[5] A generator could also sell their generation capacity or purchase energy to cover previously contracted supply obligations on this market. Then, four times every hourly interval, ERCOT equates a generator-supplied market supply curve to the instantaneous residual demand not covered by the day-ahead market and sets the market clearing price for energy subject to congestion constraints (see Teng [2004] for a technical review). This residual (or "real-time") market addresses previously unforecasted

[5]In conversations with organizations that represent consumer groups like the Texas Restaurant Association, school districts, or small factories, purchasing by retailers on the spot market without also engaging in bilateral contracts is viewed within the industry as overly risky because bankruptcy is a likely outcome due to costly demand swings.

issues such as unscheduled transmission lines maintenance, inclement weather, and such. The last-accepted bid price of a fifteen-minute interval is the uniform price paid to generators. Hortasu and Puller [2008] offer a comprehensive review of ERCOT's wholesale market mechanisms.

The ERCOT market functions as a unified market during times when the network is mostly uncongested. This means that generators and retailers can purchase energy from anywhere in the state at a uniform price. However, during times of "congestion" (or heavy demand on the network), the ERCOT system breaks apart into four geographic zones that function as individual markets.[6] The four zones are the Houston zone, the North zone, the West zone, and the South zone. Each of these zones have individual market prices during times of congestion. Only one zone needs to be affected by congestion for the market separation to occur.

1.2.2.2 Current Transmission Rate Policy

As a transmission operator, ERCOT does not set transmission rates to end consumers. These are set by the PUCT. The process of setting these rates is called a *rate case*. In these cases, firms submit evidence of their fixed and variable costs incurred over a reference year. Rate cases can be brought before

[6] This zonal concept was true during the time span of 2002 – 2010. During 2004 to 2005 ERCOT experimented with a fifth zone. After 2010, ERCOT moved to a nodal market design, which is essentially a much finer set of zonal geography when zones experience congestion. This fact does not change my analysis of the market and social welfare effects, however, which analyzes the 2002-2010 time period. This paper focuses on the timespan with four zones.

the PUCT by the transmission firm, by customers, or initiated by the PUCT [PUCT, 2013]. In my data panel I observe one instance where a rate case was initiated by the PUCT; the other four changes I observe were initiated by the respective transmission firm.

The current policy of the PUCT sets transmission rates using reference year data of consumption and costs reported by the transmission firm. During the zonal period, the wholesale market in Texas met 96 times per day — this works out to roughly 35,000 market observations per year. The regulator uses this reference year data to set a transmission rate to satisfy the legal requirement from PUCT substantive rule 25.192:

> A [transmission firm]'s transmission rate shall be calculated as its commission-approved transmission cost of service divided by the [measure of maximum usage] . . . The monthly transmission service charge to be paid by each [transmission customer] is the product of each [transmission customer's] monthly rate as specified in its [transmission rate] and the [transmission customer's] previous year's [measure of maximum usage].

where the "commission approved transmission cost of service" is defined further in the substantive rules to be a within-year fixed cost and variable costs [PUCT, 2013]. Figure 1.2 reflects this rate. Following the institutional rules, the rate schedules $\{T_{il}\}$ may be formalized as total revenue needing to satisfy total costs:

$$KT_{il}Q^M = \sum_k^K C_T(Q_k) + F \quad \forall i \tag{1.1}$$

where T_{il} is the transmission rate levied to the ith consumer type under the lth transmission firm in one time period, Q^M is a measure of the maximum quantity observed in the transmission system, $C_T(Q_k)$ is the transmission cost for the kth time interval, and F is fixed costs, including items such as capital equipment amortization and land rental. The PUCT uses as its measure the statistic of the average of the highest observed peak in each month during June through September. The institutional reasoning underlying the use of this maximum measure rather than a simple maximum is that this statistic is in comparison more robust to high demand shocks. This maximal measure is a minor departure from the standard formulation of cost-of-service rates, which uses the explicit average of costs.

Note that as specified in 1.1 the rate T_{il} does not change for each consumer type. This is true for transmission (high voltage) rates. The rate is equivalent for all consumers up to a units transformation, based on the consumer type's metering technology.[7] This practice is not always true for

[7] For the time period of 2002–2010, there were four commonly used metering technologies. The most familiar is what is used with residential consumers. Residential consumers and small businesses are charged based on the sum of all energy over a time interval; the unit of measurement is kilowatt-hours (kWh). This is the integral over the time period (a month, typically) of kilowatts demanded at every interval (kW). kW metering is the next level of sophistication; these types of meters measure both kWh consumption and the highest needed kW in a month. The third type of metering technology, due to large expense, is used with very large electricity accounts. This type is called IDR (interval data recorder),

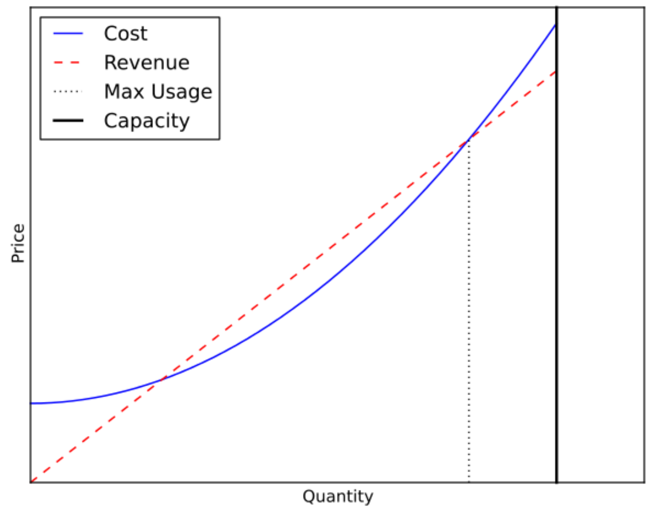

Figure 1.2: Current Pricing Regulation Example

distribution (low voltage delivery) rates: distribution costs are often divvied to consumer types by pre-assigned utility commission allocation factors (which may not reflect actual costs of a consumer type). This practice is followed by the Texas market, so each consumer type has a separate distribution rate (consumers pay both the per-unit transmission and distribution charges).[8]

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and records the observable kW flow over time. In the ERCOT area, this type of account is called a four coincidental peak (4CP) account, and is billed primarily on it's demand at the four highest summer demand peaks on the entire ERCOT system. According to the ERCOT protocols 9.8.1, the "[a]verage 4-CP is defined as 'the average Settlement Interval coincidental MW peak occurring during the months of June, July, August, and September."' and "[the] Settlement Interval MW coincidental peak is defined as the highest monthly 15 minute MW peak for the entire ERCOT Transmission Grid as captured by the ERCOT settlement system."

[8]This allocation of the distribution costs, however, is only a method of averaging distribution costs, and does not affect the actual costs accrued.

As a regulatory policy, this formalization has important economic tensions. First, by deciding the regulated rate on one reference year's worth of data, the policy is inherently backwards looking. Focusing solely on a single year of data results results in two distortions. The first distortion is the measure of the maximum may be subject to asymmetric information through selection of the transmission firm's reference year; this is of concern when the transmission firm seeks out a rate case. However, the regulator already has a wealth of information available at its disposal from ERCOT regarding the fixed and variable costs of the transmission firm. This project does not address information issues directly; instead I investigate a full-information economy. In doing so, I quantify the upper bound of potential welfare loss due to the policy decisions.

The second distortion is closely related to the first. By focusing on reimbursing variable and fixed costs in one year, the reference year data may misrepresent the likelihood of rare events such as hurricanes or droughts. Single years with multiple rare events result in overestimating the likelihood of rare events on the transmission grid; thus the regulator may set the price high. Conversely, by observing a year without any low-probability events, the transmission firm costs to be remunerated are lower than what one would find in expectation, thus the firm may be underpaid. The firm faces systemic cost overruns or profits, respectively. These costs are generally addressed through a *transmission cost recovery factor*, which takes the difference between revenue received and costs for a year, and implements an ad-hoc revenue true-up to ensure undue costs and profits are not occuring in the interim between rate cases.

The next tension is introduced through pricing by Q^M. For example, figure 1.2 shows this pricing decision where Q^M is less than a system's capacity limit. Essentially, the price is set such that the necessary transmission costs are covered at the maximal usage.[9] However, the *distribution* of possible quantity demand and supply shocks are ignored; if the mean quantity falls below the first or after the second intersections of the cost and revenue curves, then in expectation the transmission firm will run a loss. If the mean falls above the first and below the second intersection, the firm will have positive profits in expectation. By not taking into account the distribution of shocks to quantity, there is a risk that the linear mechanism will systematically result in cost overruns (requiring a transfer to ameliorate) or profits (indicating that the transmission firm is overcharging). Both of these situations are suboptimal from a social welfare maximizing perspective.

The third tension with the formulation is that because electricity operates on a network and supply must always equal demand, changing one group's transmission rate indirectly affects the quantity decision for all other transmission consumer types. This is intuitive since if the regulator increase consumer type i's rate with firm l, then consumer type i faces higher combined price. The consumer type then decreases their consumption. Decreased

[9]Within ERCOT, this measure of maximum usage is an average of summer's monthly highest usage.

consumption results in suppliers charging less for their production. Lowering the overall market price results in other consumers not in consumer group i with firm l facing lower prices, who then can consume more than before due to the lower price. This network demand shift is ignored by the current policy. This increased demand results in higher costs to transmission firms.

The fourth is related implicitly to the third. The transmission price implemented typically charges the same rate across consumer types within the same transmission firm. This practice ignores the demand elasticity of different consumer types. The standard arguments for this practice is that charging different consumer types the same price is nondiscriminatory and fair [U.S. Federal Energy Regulatory Commission, 1996]. However, allowing some price discrimination on the basis of each consumer type's price elasticity of demand can be welfare-enhancing. In setting the price to be equivalent across types by transmission firm, the regulator implicitly subsidizes inelastic consumers at the expense of more elastic consumers. This results in institutionalized misallocations of energy.

1.3 Model

In this section I formalize the interactions between generators, retail consumers, regulators, and transmission firms. This allows a decomposition of the previously discussed tensions and to estimate the relative welfare effects on participants in the electricity market. This is accomplished by using a full information model. This full-information assumption is one that can be scrutinized; certainly there is potential in which a regulated firm, because it is guaranteed a certain return on costs, represents a moral hazard for the regulator. Further, one may be concerned regarding the Averch-Johnson effect in that the firm chooses to overcapitalize in its production input ratio. Despite this potential charge the full-information assumption still has merit—this model captures the upper bound of welfare losses under the policy. Additionally, the regulator in my model operates in lock-step with the operator. This is fairly realistic—there is full information sharing between ERCOT and the PUCT. As such, the regulator knows how much electricity is going to where at any given point in the network. Additionally, there is quarterly cost reporting by the regulated firm to the Federal Energy Regulatory Commission. Further, typical large expenses such as network expansion must be approved by the PUCT, which may give the regulator a dynamic advantage through information ratcheting. Finally, the PUCT and ERCOT draw from the same human capital pool as transmission firms. This means the regulator, with full information of the network topology, can determine variable costs of the network.

1.3.1 Model Introduction

In this section I discuss the actors and available actions in the model. The actors include generators, consumers, the regulator, and a set of transmission firms. I model the transmission firms as passive model participants that move energy. They do not participate directly in the wholesale market;

instead, the firms are required to move any quantity over the transmission network.

Consumers and generators have supply and demand curves dependent on some state s of the world. Here s denotes states differentiated by supply and demand shocks; each of these states occur with probability π_s. Consumers are partitioned by type i, transmission firm l, and geographic market z. Individual consumers of type i consume the same amount of energy under the same conditions, regardless of geographic market or transmission firm. The number of consumers of type i in market z under transmission firm l is represented by σ_{ilz}. When i and l are used to specifically refer to one consumer type under one transmission firm, I will use j and m to refer to other types and companies, respectively.

The regulator may set the per-unit price T_{il} for each ith consumer type under firm l. This price is the transmission rate charged for one unit of energy regardless of realized state of the world s. The total menu of rates is denoted as T.

Generators provide supply for each zone. Suppliers face generation costs $C_g(\cdot)$ across all zones and receive payment $p_z(T, s)$ for each unit purchased within zone z. The transmission firms face costs $C_l(\cdot)$ and fixed F_l and receive a linear tariff T_{il} for delivery for consumer of type i. I denote the marginal costs of transmission firms and generators with respect to quantity as C_l' and C_g' respectively.

The quantity demanded in zone z for transmission firm consumers of type il in state s is $\sigma_{ilz} q_i(p_z(T_{il}, s) + T_{il}, s)$. Let total zone market quantity be the sum of all i type demands,

$$Q_z(p_z(T, s), T, s) = \sum_i \sum_l \sum_z \sigma_{ilz} q_i(p_z(T, s), T_{il}, s). \tag{1.2}$$

Similarly define $Q_l(p(T, s), T, s)$ as the sum of all quantity in transmission firm l's network across all zones.

To simplify notation, when the expectation operator $\mathbb{E}(\cdot)$ is used, the state notation s is suppressed (e.g. $\sum_s \pi_s p_z(T, s) \equiv \mathbb{E}(p_z(T))$). Denote the derivative of each $q_i(p_z(T, s) + T_{il}, s)$ with respect to its first argument q'_{ilz}. Additionally, if prices across all zones or the entire transmission rate schedule are referred to, p or T respectively are used without subscripts.

The instantaneous social welfare function for a single k interval is the sum of gross consumer surplus, generator revenue, and transmission firm revenues less gross costs for generation and transmission. Social welfare in state

s is formulated as[10]:

$$SW(T,s) =$$
$$\Bigg\{\sum_z \Bigg[\sum_l \sum_i \sigma_{ilz}\Bigg(\underbrace{\int_{p_z(T,s)+T_{il}}^{\infty} q_i(p)dp}_{\text{Consumer Surplus}} + \underbrace{(p_z(T,s)+T_{il})q_i(p_z(T,s)+T_{il},s))}_{\text{Producer and Transmission Revenue}}\Bigg)$$
$$- \underbrace{C_l(Q_l(p,T,s)) - \frac{F_l}{K}}_{\text{Transmission Costs}}\Bigg]\Bigg\} - \underbrace{C_g(Q(p,T,s))}_{\text{Generator Costs}} \tag{1.3}$$

The derivative of social welfare with respect to T_{il} in state s is:

$$\frac{\partial SW(s)}{\partial T_{il}} = \sum_z \Bigg[\underbrace{\sigma_{ilz}(p_z(T,s)+T_{il}-C'_g-C'_l)q'_{ilz}}_{\text{Direct effect}}$$
$$+ \underbrace{\sum_m \sum_j \Bigg(\sigma_{jmz}(p_z(T,s)+T_{jm}-C'_g-C'_m)q'_{jmz}\frac{\partial p_z}{\partial T_{il}}\Bigg)}_{\text{Indirect Effects}} \tag{1.4}$$

The implications of this derivative run counter to the current literature on cost-of-service regulations because a change in tariff affects not only consumers directly under firm l's geographic monopoly but also all consumers in the same connected network under other transmission firms from firm l's consumers. The direct effect in the market for consumers of type i under firm l is a negative decrease to social welfare. However, lowered demand for consumers results in lower first-order quantity demands; suppliers respond by decreasing the price of the market (denoted by $\frac{\partial p_z}{\partial T_{il}}$). Consumers of every type

[10]The formulation for consumer i surplus uses ∞ as the upper integral bound here; this is a slight abuse of notation. The integral bound is simply where the demand function crosses the y-axis.

respond to this first-order decrease in prices with a second-order increase in demand. This means social welfare can respond ambiguously to a change in one firm's tariff rate schedule. There is an implicit bound here for the change in price with respect to a transmission rate $\frac{\partial p_z}{\partial T_{il}}$ must be within the interval $[-1, 0]$. This bound is required for the law of demand—increasing a price does not result in more demand for it by a consumer. Further, to increase price to its level before the tariff change would require some customer type j to allocate more than the entire benefit of the price change to the consumption of energy—indicating the customer type was not optimizing before the price change, all else equal.

Proposition 1.3.1. *The change in price with respect to a single group's rate is bounded between -1 and 0.*

Proof. From the model primitives, supply in each zone Q_z must equal demand in each zone, $\sum_m \sum_j \sigma_{jmz} q_j(p_z(T) + T_{jm})$. Thus

$$Q_z(P(T)) = \sum_m \sum_j \sigma_{jmz} q_j(p_z(T) + T_{jm}) \tag{1.5}$$

The derivative of both sides gives

$$Q'_z \frac{\partial p_z}{\partial T_{il}} = \sigma_{ilz} q'_{ilz} + \sum_m \sum_j \sigma_{jmz} q'_{jmz} \frac{\partial p_z}{\partial T_{il}} \tag{1.6}$$

which can be transformed into

$$\frac{\partial p_z}{\partial T_{il}} = \frac{\sigma_{ilz} q'_{ilz}}{Q'_z - \sum_m \sum_j \sigma_{jmz} q'_{jmz}} \tag{1.7}$$

For each consumer, demand response $q'_{jmz} < 0$. Supplier response is positive. Hence the right-hand side is negative. Further, q'_{ilz} is in both the denominator and the numerator. Thus, the change in price with respect to il's rate is bounded between $[-1, 0]$ $\square$

An intuitive way to think of this proposition is that the wholesale market does not shoulder more than 100 percent of impact of transmission fee changes.

Given transmission rates, the generators and consumers engage in trade where, as mentioned before, each il consumer pays $p_z(T) + T_{il}$ for each unit of energy and generators receive p_z. The optimal equilibrium which considers all aspects of this model occurs when transmission rates are set so as to maximize expected social welfare.

The first-best solution in this setup is straightforward—set transmission rates T_{il} to marginal transmission costs and charges a fixed fee f_{il} for each consumer type.[11] I assume here transmission is routed optimally by the operator.

1.3.2 Derivation of Ramsey pricing rule

Under a second-best pricing setup, the regulator faces constraints for each l transmission firm of ensuring expected prophets surpass known fixed

[11]The political economy question of optimal fixed fee assignment are outside the specific scope of this project.

costs

$$\mathbb{E}\left[\underbrace{\sum_i T_{il}\left(\sum_z \sigma_{ilz} q_i(p_z(T)+T_{il})\right)}_{\text{Transmission Revenue}} - \underbrace{C_l(Q_l(p,T))}_{\text{Transmission Costs}}\right] \geq \frac{F_l}{K} \tag{1.8}$$

where K is the total number of times the market meets. If revenues do not exceed costs in expectation, a transmission firm risks cost overruns and bankruptcy.

Using the setup above, we have the objective function

$$\max_{\{T_{il}\}} \quad \sum_s \pi_s SW(T,s) \tag{1.9}$$

subject to

$$\mathbb{E}\left[\sum_z \sum_i \sigma_{ilz} q_{il}(p_z(T)+T_{il})T_{il} - C_l(Q_l(P,T))\right] - \frac{F_l}{K} \geq 0 \quad \forall\, l \tag{1.10}$$

where K is the number of occasions the wholesale market meets for the time period the transmission rate covers.

FOC for this problem are

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial T_{il}} &= \mathbb{E}\Bigg\{\sum_z \sigma_{ilz}(p_z + T_{il} - C'_g - C'_l)q'_{ilz} \\
&\quad + \left[\sum_m \sum_j \left(\sigma_{jmz}(p_z + T_{jm} - C'_g - C'_m)q'_{jmz}\frac{\partial p_z}{\partial T_{il}}\right)\right]\Bigg\} \\
&\quad + \lambda_l \mathbb{E}\left\{\sum_z \sigma_{ilz} q_i(p_z + T_{il}) + (T_{il} - C'_l)\sigma_{ilz} q'_{ilz}\right\} \\
&\quad + \sum_m \lambda_m \mathbb{E}\left\{\sum_j \sigma_{jmz}(T_{jm} - C'_m)q'_{jlz}\frac{\partial p_z}{\partial T_{il}}\right\} \leq 0
\end{aligned} \tag{1.11}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_l} = \mathbb{E}\Bigg\{\sum_z \sum_j \sigma_{jlz} q_i(p_z + T_{il}) - C_l(Q_l(p,T))\Bigg\} - \frac{F_l}{K} \geq 0 \tag{1.12}$$

where λ_l is the Lagrangian multiplier on the budget balance equations 1.12.

From these FOC, one derives the optimal policy T^* and Lagrangian multiplier λ^*:

$$
\begin{aligned}
T^*_{il} = &\underbrace{\frac{-\lambda_l}{1+\lambda_l}}_{\text{Scaling Factor}} \underbrace{\frac{\mathbb{E}\left(\sum_z \sigma_{ilz} q_i (p_z + T_{il})\right)}{\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Inverse elasticity}} - \underbrace{\frac{\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (p_z - C'_g)\right)}{(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Direct Market Effect}} \\
&+ \underbrace{\frac{\mathbb{E}\left(C'_l \sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}{\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Marginal Transmission Cost}} - \underbrace{\frac{\mathbb{E}\left(\sum_z \sum_{j,m \neq il} (1+\lambda_m) T_{jm} \sigma_{jmz} q'_{jmz} \frac{\partial p_z}{\partial T_{il}}\right)}{(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Interaction with other transmission firms}} \\
&- \underbrace{\frac{\mathbb{E}\left(\sum_z \sum_m \sum_j \sigma_{jmz} q'_{jmz} (p_z - C'_g - (1+\lambda_m) C'_m) \frac{\partial p_z}{\partial T_{il}}\right)}{(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz} (1 + \frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Indirect Market Effect}} \qquad (1.13)
\end{aligned}
$$

and λ^* solves

$$
\Omega T^* = \Upsilon \qquad (1.14)
$$

where Ω is a matrix with elements

$$
\omega_{jm,il} = (1+\lambda_m)\mathbb{E}\left[\sum_z \sigma_{jmz} q'_{ilz} \left[\frac{\partial p_z}{\partial T_{il}}\right]\right] \qquad (1.15)
$$

$$
\omega_{il,il} = (1+\lambda_l)\mathbb{E}\left[\sum_z \sigma_{jmz} q'_{ilz} \left[\frac{\partial p_z}{\partial T_{il}} + 1\right]\right] \qquad (1.16)
$$

and Υ is a vector of the same length as T^* with elements

$$\begin{aligned}
\upsilon_{il} = \mathbb{E}\left(C_l' \sum_z \sigma_{ilz} q_{ilz}'\right)(1+\lambda_l) - \lambda_l \mathbb{E}\left(\sum_z \sigma_{ilz} q_i (p_z(T) + T_{il})\right) \\
+ \sum_m (1+\lambda_m) \sum_j \left(C_m' \sum_z \sigma_{jmz} q_{jmz}' \frac{\partial p_z}{\partial T_{il}}\right) \\
- \mathbb{E}\left(\sum_z \left(p_z(T) - C_g'\right) \sum_m \sum_j \sigma_{jmz} q_{jmz}' \frac{\partial p_z(T)}{\partial T_{il}}\right) \\
- \mathbb{E}\left(\sum_z \left(p_z - C_g'\right) \sigma_{ilz} q_{ilz}'\right)
\end{aligned} \tag{1.17}$$

Further, (T^*, λ^*) solve

$$\mathbb{E}\left\{\sum_z \sum_j \sigma_{jlz} q_i (p_z + T_{il}^*) - C_l(Q_l(p, T^*))\right\} = \frac{F_l}{K} \quad \forall l \tag{1.18}$$

which are the respective budget constraints for each individual firm.

Equation 1.13 is the implicit functional form of equation 1.14. From equation 1.13 we see that the optimal price is not just the marginal cost — there is an optimal increase based on scaled elasticity, and an accounting for the impact the tariff change has on the wholesale market (market interference effect and indirect type demand effect). Except for the scaling on quantity, each component of the right hand side is the weighted average with each component weighted by its relative change on the overall market. This term one can see in the denominator as $\sum_z \sigma_{ilz} q_{ilz}' (\frac{\partial p_z}{\partial T_{il}} + 1)$.

The Lerner index adds some additional insight into the optimal transmission rate markup:

$$\underbrace{\frac{T^*_{il} - \frac{\mathbb{E}(\sum_z C'_l \sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{ilz}})}{\mathbb{E}(\sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{il}}))}}{T^*_{il}}}_{\text{Lerner Index}} = \frac{-\lambda_l}{1+\lambda_l} \underbrace{\frac{\mathbb{E}\left(\sum_z \sigma_{ilz} q_i (p_z + T_{il})\right)}{T^*_{il}\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Elasticity of demand}}$$

$$-\underbrace{\frac{\mathbb{E}\left(\sum_z \sum_{j,m\neq il}(1+\lambda_m)T_{jm}\sigma_{jmz}q'_{jmz}\frac{\partial p_z}{\partial T_{il}}\right)}{T^*_{il}(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{il}})\right)}}_{\substack{\text{Interaction with revenue from other customer} \\ \text{types in all connected transmission firms}}} - \underbrace{\frac{\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz}(p_z - C'_g)\right)}{T^*_{il}(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Direct Market Effect}}$$

$$-\underbrace{\frac{\mathbb{E}\left(\sum_z \sum_{j,m\neq il}\sigma_{jmz}q'_{jmz}(p_z - C'_g - (1+\lambda_m)C'_m)\frac{\partial p_z}{\partial T_{il}}\right)}{T^*_{il}(1+\lambda_l)\mathbb{E}\left(\sum_z \sigma_{ilz} q'_{ilz}(1+\frac{\partial p_z}{\partial T_{il}})\right)}}_{\text{Indirect effect on generator markups and costs}}$$

The Lerner index shows us the optimal deviations from marginal cost pricing. This formulation of the Lerner index is significantly different than what one finds in a standard model of regulated monopolies. First, the inverse elasticity is scaled down by $\frac{\lambda_l}{1+\lambda_l}$, which is the canonical Ramsey-Boiteux pricing result. However, since transmission is the delivery mechanism with the wholesale market resting atop of it, there are other effects that a social-welfare maximizing regulator must take into account. In addition to the standard Ramsey-Boiteux scaling of inverse elasticity, the Lerner index is decreased by the direct market effect. This direct effect may be offset or augmented by the indirect market effect, depending on the relative magnitudes of the λ_l terms. Finally, the Lerner effect is affected by the interaction of other customer types and firm transmission rates; this effect is positive in the first-order effect, but is ambiguous in the second order.

1.3.3 An Example

To give a concrete example of calculating second-best rates in this abstract model, consider an example with two states of the world, two consumer types, and one transmission firm. The first consumer type a has a highly variable demand, and type b has a less varying demand. There are two states of the world high and low, denoted $\{H, L\}$. Costs of transmission are $C_T(Q) = cQ^2$, and costs of generation are $C_g(Q) = gQ$. State H occurs with probability p

Consumer types a and b are characterized in states of the world s within the set $\{H, L\}$ by

$$Q_{as} = A_s - p(T, s) - T_a \tag{1.19}$$

$$Q_{bs} = B_s - p(T, s) - T_b \tag{1.20}$$

which, for each state s, gives total market demand

$$Q_s = A_s + B_s - 2p(T, s) - T_a - T_b \tag{1.21}$$

For simplicity, I assume only demand shocks, so the supply function is deterministic and is represented by the simple function

$$Q^{sup}(P, T_a, T_b) = P(A_s, B_s, T_a, T_b). \tag{1.22}$$

Using the condition that supply must equal demand, we can solve for prices directly:

$$Q_s = Q^{sup} \tag{1.23}$$

$$\rightarrow A_s + B_s - 2P(A_s, B_s, T_a, T_b) - T_a - T_b = P(A_s, B_s, T_a, T_b) \tag{1.24}$$

$$\rightarrow P(A_s, B_s, T_a, T_b) = \frac{A_s + B_s - T_a - T_b}{3} \tag{1.25}$$

The objective function is

$$\begin{aligned}
\max_{T_a, T_b} \quad & \underbrace{p(.5[Q_{ah}^2 + Q_{bh}^2]) + (1-p)(.5[Q_{al}^2 + Q_{bl}^2])}_{\text{Consumer Surplus}} \\
& + \underbrace{p \cdot P(A_h, B_h, T_a, T_b)^2 + (1-p) \cdot P(A_l, B_l, T_a, T_b)^2 - g(pQ_h + (1-p)Q_l)}_{\text{Generator Profit}} \\
& + \underbrace{\cdot [p(T_a Q_{ah} + T_b Q_{bh} - cQ_h^2) + (1-p)(T_a Q_{al} + T_b Q_{bl} - cQ_l^2)] - F}_{\text{Transmission Profit}}
\end{aligned} \tag{1.26}$$

subject to

$$T_a(pQ_{ah} + (1-p)Q_{al}) + T_b(pQ_{bh} + (1-p)Q_{bl}) \geq c(pQ_h^2 + (1-p)Q_l^2) + F \tag{1.27}$$

where equation (1.27) is the budget-balance constraint for the transmission firm.

The Lagrangian is

$$\begin{aligned}
\mathcal{L} = {} & p(.5[Q_{ah}^2 + Q_{bh}^2]) + (1-p)(.5[Q_{al}^2 + Q_{bl}^2]) + p \cdot P(A_h, B_h, T_a, T_b)^2 \\
& + (1-p) \cdot P(A_l, B_l, T_a, T_b)^2 - g(pQ_h + (1-p)Q_l) + T_a(pQ_{ah} + (1-p)Q_{al}) \\
& + T_b(pQ_{bh} + (1-p)Q_{bh}) - c \cdot [pQ_h^2 + (1-p)Q_l^2] - F \\
& + \lambda(T_a(pQ_{ah} + (1-p)Q_{al}) + T_b(pQ_{bh} + (1-p)Q_{bl}) - c(pQ_h^2 + (1-p)Q_l^2) - F)
\end{aligned} \tag{1.28}$$

The current cost-of-service rule takes historic data on variable and fixed costs and sets the same price for both consumer types. To simulate this process, I draw $k = 20$ realizations of h or l from a Bernoulli distribution to serve as a historical observation of previously observed costs. This draw gives us a random rate T equal to

$$T = \frac{\sum_{k=1}^{20} C_T(Q_{s_k}) + F}{20 \cdot Q^h} \tag{1.29}$$

where T is the rate the cost of service rule recommends. I take a sample of 300 histories and use the average suggested rate.[12] I repeat this exercise for rates between covering the interval $[0, 4]$.

To illustrate the solution to this programming problem versus the current policy, I use the parameterization in table 1.2. I repeat the exercise for two cases: one where the the high state is more likely, and one where the low state is more likely. The results of these parameterizations highlight the institutionalization of winners and losers under a cost of service rule relative to a Ramsey-Boiteux pricing benchmark, as well as the high likelihood of implementing a COS rule that runs counter to the goals of the regulator. Numerical results for this model are found in table 1.3. The first column corresponds to our optimal linear rate. The second column adheres to the cost of service policy at the best possible welfare result for the probability parameterization. The graphical results found in figures 1.3 and 1.5 expand the cost of service rate analysis to the interval $[0, 4]$.

[12] Histories consist of 20 draws with $P(high) = p$.

Table 1.2: Simple Example Parameterization

Parameter Name	Parameter Value
Periods k	20
High intercept for A	17
Low intercept A	10
High intercept for B	10
Low intercept B	8
Generator cost g	2
Transmission cost c	.3
Fixed cost F	60
Probability p	.9, .1

The two sub-tables in table 1.3 report the model outcomes when probability p is .9 and .1, respectively. The first column reports the optimal linear rate results for both consumers A and B. The second column reports the optimal cost-of-service rate results without regard to the historical rate as input into the COS rule. In effect, the second column is comparing the optimal rule to a rule that does not distinguish between consumer types. The first observation is that expected net social welfare under the two rules changes by less than 1% for each other probability run reported. This small magnitude is robust to other specifications of probability; the difference in welfare generally increases with an increase in p. This small difference in welfare is accounted for by the relatively large slopes of the total demand (slope is 2) versus supply (slope is 1) in both states. The second observation is that the winners under the COS regime are transmission firms and consumer type A, and the losers are generating firms and consumer type B. The consumer surplus loss to type B ranges between 20 percent to 82 percent depending on state and probability.

Variable	1	2
Tariffs (T_a,T_b)	(2.74, 1.68)	(2.57, 2.57)
Expected Net Welfare	62.55	32.05
Transmission Firm Expected Profit	0	1.373
Price in High State	7.52	7.29
Price in Low State	4.52	4.29
Generator Profits High State	41.55	38.52
Generator Profits Low State	11.41	9.81
Consumer (A , B) Surplus in High State	(22.64, .31)	(25.51, .01)
Consumer (A , B) Surplus in Low State	(3.72, 1.61)	(4.94, .65)
Quantity (A , B) in High State	(6.73, .795)	(7.14, .14)
Quantity (A , B) in Low State	(2.73, 1.795)	(3.14, 1.14)
1. Optimal Linear Rule		
2. Best COS Outcome		
$p = .9$		

Variable	1	2
Tariffs (T_a,T_b)	(2.25, 1.85)	(2.13, 2.13)
Expected Net Welfare	23.22	23.155
Transmission Firm Expected Profit	0	.14
Price in High State	7.63	7.58
Price in Low State	4.63	4.58
Generator Profits High State	42.983	42.296
Generator Profits Low State	12.191	11.816
Consumer (A , B) Surplus in High State	(25.31, .13)	(26.57, .04)
Consumer (A , B) Surplus in Low State	(4.85, 1.149)	(5.41, .832)
Quantity (A , B) in High State	(7.12, .52)	(7.29 , .29)
Quantity (A , B) in Low State	(3.12, 1.52)	(3.29, 1.29)
1. Optimal Linear Rule		
2. Best COS Outcome		
$p = .1$		

Table 1.3: Simple Example Outcomes with $p = .9$ and $p = .1$

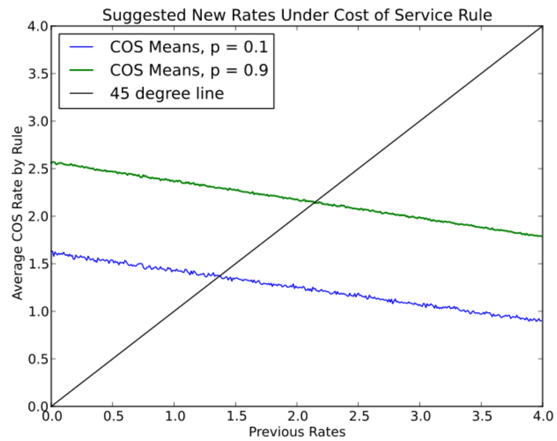


Figure 1.3: Cost of Service Rates required by Historical Rates

While the total gain to consumer A is larger than the loss to consumer B, percentage gains are much smaller. The third observation is that the transmission firm receives a profit under the COS rule when we look for welfare maximizing rates. However, this finding is not robust to all probability specifications, and the optimal COS option may require a history with a rate that is infeasible. Figure 1.3 shows the historical rate required for a specific COS rule to be implemented. The forty-five degree line in figure 1.3 is included to determine fixed points the COS rule would converge to if followed through time. In the simple example, both fixed points result in institutionalized cost overruns on the part of the transmission firm, which we see in figure 1.5. This would be considered infeasible based on the primitives of the model since an institutionalized cost overrun would require a transfer to the transmission utility for it to stay solvent.

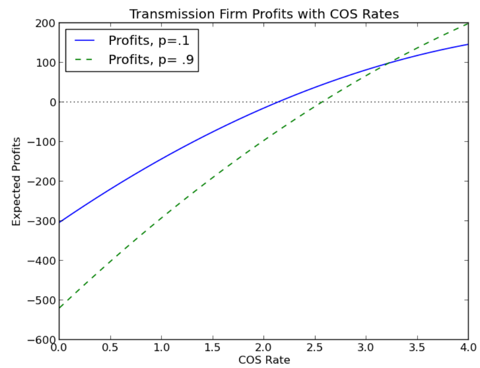


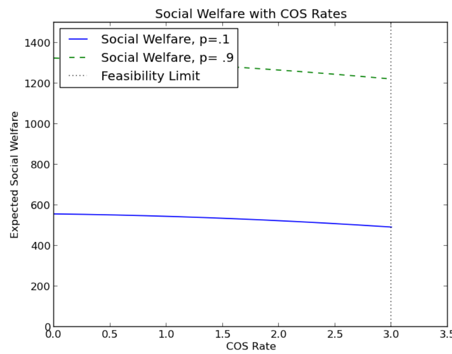
Figure 1.4: Profits of Transmission Firm under COS Rates

Figure 1.5 shows the social welfare impact under each probability specification of not allowing a transfer under a COS rule.[13] Subfigures 1.5(a) and 1.5(b) are similar, but figure 1.5(b) shows the listing of feasible options when transfers are institutionally disallowed.

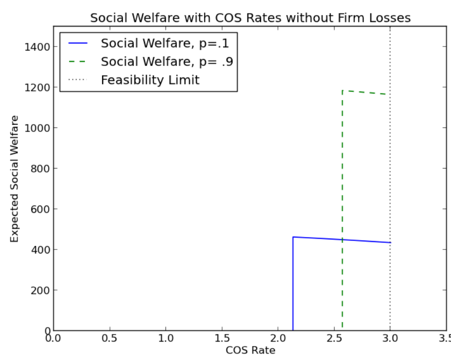
In these two figures, regardless of the previous COS rate, the optimal rate gives welfare of 1251 for $p = .9$ and 464.4 for $p = .1$. While infeasible (without transfer) COS rates may allow for a higher expected social welfare, feasible rates all fall under these amounts.

This example gives the intuition that is used while applying the model to the empirical setting of the Texas electricity market. The key points are that: 1) individual consumer types may be worse off depending on the state distribution, but net consumer welfare will be higher overall; and 2) COS rates

[13]Rates above 3 under either specification result in a corner solution as consumer type Bs linear demand requires negative consumption for rates above this value.



(a) Social Welfare, With Transfer



(b) Social Welfare, No Transfer

Figure 1.5: Social Welfare under COS Rates

may result in infeasible fixed points requiring transfers.

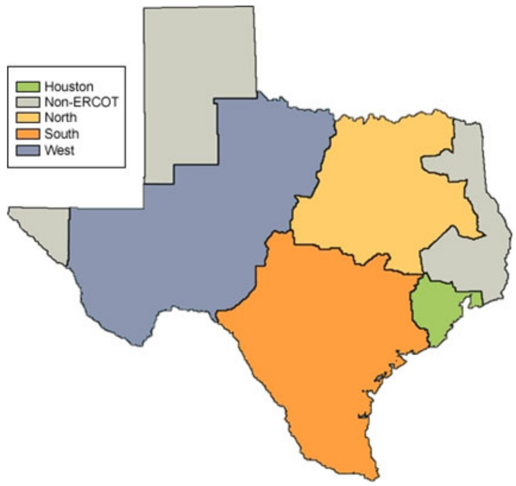
1.4 Data

To analyze the effects of transmission rates on the welfare market, I compile a comprehensive dataset using data on market quantity, price, transmission rate and cost information, hourly weather conditions, generation emissions output, and energy production input prices.

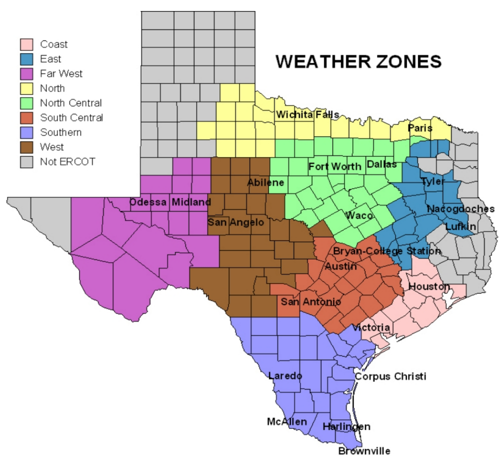
Quantity by consumer type within ERCOT is reported in megawatt-hour units at the quarter-hour level. The data are partitioned by four distinct factors: network zone, weather zone, transmission firm, and consumer type. Defined by ERCOT, network zones and weather zone are geographic partitions. Zones correspond to the model as z; most covariates correspond to z and weatherzones, which gives a finer partition. Weather zones are based on areas that share a similar climate, including temperature and relative humidity. Network zones are based on the transmission network topology; ERCOT operates markets at the zonal level. Weather zones partitioning is independent of network zones. Figure 1.6 details these partitions by network zone and weather zone within the ERCOT area.[14]

Transmission firms are based on geographic location. Consumer types are based on observable characteristics. For this paper I aggregate among ERCOT-denoted types to map between tariffs and quantity data. The group-

[14]The maps do not include an additional zone extant from 2004 – 2006.



(a) ERCOT zones



(b) ERCOT Weather Zones

Figure 1.6: ERCOT partitions, 2002 – 2004, 2007 – 2010
Source: ERCOT

ing I use is residential (RES) and business/industrial types. Business/industrial types are further subdivided by relative size into small accounts not requiring a demand meter (BUSNO), large accounts requiring an interval data recorder (BUSIDR), and other kinds of accounts (BUS). The data on BUS quantity consumption does not distinguish primary versus secondary transmission consumers, which is an important distinction in transmission firm rates.[15] To alleviate this potential difficulty I use a weighted average of tariffs for each PUC consumer type in the BUS, BUSNO, and BUSIDR ERCOT groups. Table 1.4 shows the relationship between ERCOT groups and PUC types.

The number of accounts for each consumer type by transmission firm are recorded quarterly and can be found in ERCOT's *Load Profiling Profile Type Count*. These are broken down by weather zone and geographic zone. The average consumption and population deviation for each consumer type in each zone are listed in table 1.5. From the information presented in this table I observe that the average consumption for each consumer type in each zone is not significantly different from other zones; I use this fact later in the empirical section to estimate average consumption as a function of prices and covariates.

Wholesale zone prices are derived from ERCOT's *Balancing Energy Services* energy curve outcome for the real-time (residual) demand market. This market takes supply-curve bids for providing more (up-balancing) or pro-

[15]The technical difference is which side of the transformer the electric meter is on. Some consumers, such as factories, opt to maintain their own transformer equipment.

Table 1.4: Mapping of ERCOT and PUCT Consumer Types

Data Type	ERCOT Type	PUCT Type	Method of Tariff Averaging
BUS	All BUS types, including solar- and wind-supplemented customers, and customers with varying load factors*	Secondary and Primary service with monthly demand service	Weighted
BUSNO	All BUSNO types, including solar and wind customers	Small Secondary Service or Primary Service without demand metering	Not required
BUSIDR	All BUSIDRRQ accounts	Large Secondary Service, Primary service with IDR	weighted average based on rate-case customer account counts
RES	All RES types, including solar and wind customers	No aggregating necessary	Not required

viding less (down-balancing) energy into the system. Within the hour, ERCOT chooses at every fifteen minute interval the balancing supply required. This is represented in figure 1.7. If additional quantity over Q_0 is required to keep supply equal to instantaneous demand, ERCOT sets the price at the corresponding P. Similarly, if less quantity is required, then ERCOT sets the spot market price lower. This can result in negative prices observed in spot market prices. The value of the contracted price P_0, unknown to the econometrician, lies somewhere along the Q_0 axis. This axis is where no energy is supplied into

Table 1.5: Hourly Consumption by Consumer Type in kWh

Consumer Type	Houston Zone	North Zone	South Zone	West Zone	East Zone*
RES	1.89	1.74	1.58	1.98	1.73
	(1.05)	(1.46)	(1.05)	(1.27)	(.91)
BUSNO	2.56	.659	.831	.673	.606
	(5.04)	(.343)	(2.09)	(.431)	(.367)
BUS	14.10	16.92	10.20	10.29	11.82
	(8.26)	(19.17)	(7.20)	(8.24)	(8.38)
BUSIDR	1553.31	1102.41	1321.00	1162.18	1947.88
	(1433.91)	(1784.07)	(896.29)	(1091.86)	(2690.32)

* The East Zone only existed from 2004 through 2006. Before that consumer groups were part of the North and Houston zones. Unit is 15-minute interval.

the residual market. To recover P_0 for each zone I take the weekly average of all aggregate residual zonal market supply observations where prices lies along the Q_0 axis — this is where no additional energy is required in the residual market, and so matches the forward and futures market outcome. This price P_0 is constant across all types, transmission firms, and weatherzones within a zone. As can be observed in figure 1.7, the support in a single observation for this contracted P_0 may be negative, and indeed in spot market price outcomes one does occasionally observe negative values. As one sees in 1.6, however, these potential negative contracted prices are not observed within the imputed data. One notes that the West zone faces significantly skewed prices in comparison to the others zones. This could be accounted for by the nature of industrial demand in West Texas: oil and natural gas operations can

Figure 1.7: Residual market example

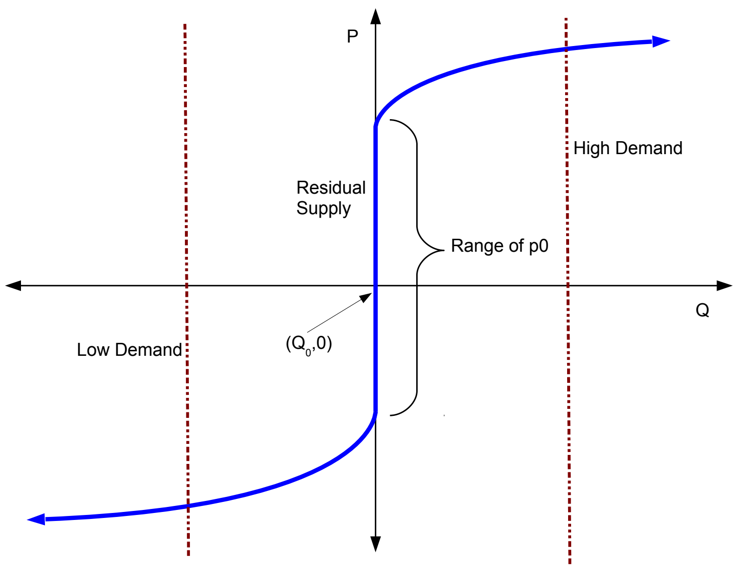


Table 1.6: Price Summary

Zone	Average Price	Standard Deviation	Median Price	Max Price	Min Price	75% Price	25% Price
Houston	43.22	(15.38)	41.32	101.52	10.32	51.15	32.33
North	41.96	(14.60)	39.85	97.00	11.95	47.90	31.98
South	40.17	(15.47)	37.93	101.31	9.79	46.20	29.72
West	76.18	(71.71)	58.97	645.1058	9.74	100.11	29.55

be extremely energy intensive.[16]

Climate data is available from NOAA weather station hourly reports. Data used include Fahrenheit dry-bulb temperature and relative humidity index readings. These data come from the primary weather stations for major cities within each ERCOT-defined weather zone. When looking at zonal information, such as supply, the average weather zone weather information is used (weighted by customer counts of each type in each weather zone within the zone). In demand specifications I use heating-degree-days (HDD) and and cooling-degree-days (CDD). HDD is defined as

$$HDD = (65^\circ - F^\circ) \cdot \mathbf{1}(F^\circ < 65^\circ) \tag{1.30}$$

where F° is the degrees in Fahrenheit and $\mathbf{1}(\cdot)$ is an indicator function. A CDD is defined as the inverse relationship:

$$CDD = (F^\circ - 65^\circ) \cdot \mathbf{1}(F^\circ \geq 65^\circ) \tag{1.31}$$

Figure 1.8 shows a clear non-monotonic relationship between temperature and equilibrium quantity outcomes. This is a well-known relationship and is quite intuitive. As temperature increases, air-conditioning demand increases (fueled primarily by electricity). As temperatures decrease, heating demand increases (fueled by either electricity or substitutes such as gas or firewood). Because instrumental variables need to be monotonic, use of HDD and CDD allow one to separate out this non-monotonic effect within an IV framework.

[16] It could also be due to constrained transmission imports into the West zone.

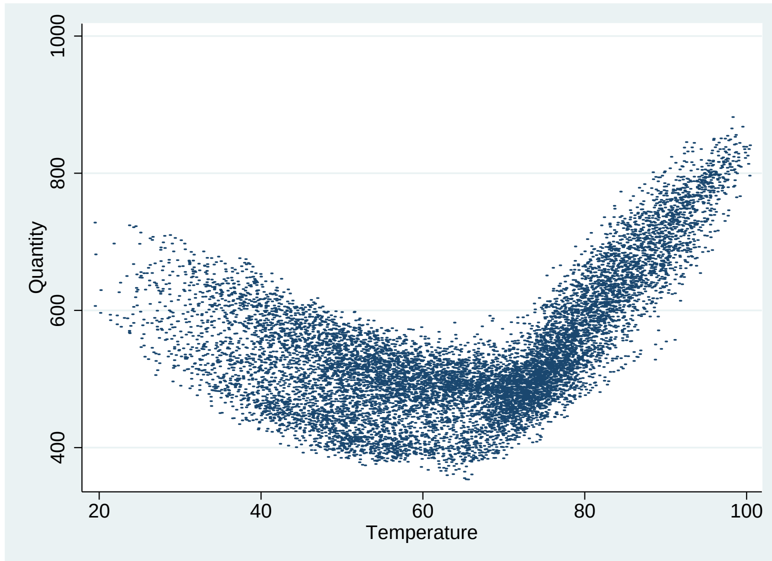


Figure 1.8: Temperature and Quantity Scatterplot
West Zone

Data for the marginal cost of electricity generation can be inferred from emissions data following a modification of the method of Puller [2007] (and also building from marginal fuel costs method of Kahn et al. [1997]). The EPA Air Markets Program Data contains hourly information for fossil-fuel using generators on emissions and generation. The marginal cost is the sum of emissions permits (SO2 and NOX), fuel, and variable O&M costs. I supplement this output data with monthly average nuclear output from the EIA (nuclear generators are expensive to increase or decrease production) and engineering estimates of variable O&M costs available from ERCOT. Fuel input marginal costs are assumed to be linear, and are calculated based on generator megawatt output multiplied by engineering efficiency rates (MMBTU/kWh) for the station, or an EIA standard efficiency rate if the specific generator rating is unavailable. The result is then multiplied by per-unit fuel prices for the fuel type and output at the period of measurement. To this I add the variable operating and maintenance (O&M) costs for the generator. I then find the market marginal cost using an assumption of allocative efficiency.[17] This represents the intensive market generation marginal cost.

Transmission firm data for fixed and variable costs are available from the Federal Energy Regulatory Commission (FERC). Transmission costs for most IOU firms are available over the time span of 2004 to 2010 at a quarterly interval and from 1994 to 2011 at an annual interval. One company, CenterPoint, has only annual data, and another, Texas-New Mexico Power, ceased to provide information after 2006. Transmission rates are available from the PUCT in rate case docket final orders and from a biannual report. The PUCT identifies six specific categories for transmission consumers (mapped in table 1.4): residential, small commercial, large secondary commercial, large primary commercial, transmission service, and unmetered (which are typically street lighting and traffic signals). I define consumer types along these dimensions. Within the data I focus on the largest subset of these categories: residential, small commercial, secondary commercial, and large primary commercial. [18]

[17]This assumes no regulatory or reliability-must-run service.

[18]Transmission service is service provided for other transmission providers (i.e. power to distribution providers not under direct transmission firm ownership—this revenue is included in the abstraction as costs to other transmission firms). This is required for "open access"

1.5 Empirical Strategy

This section summarizes the empirical strategy used to recover model behavioral parameters and welfare outcomes. I first use instrumental variables to determine demand and supply responsiveness to price and exogenous variables. I also estimate a parameterized form of each firms' average variable transmission cost function. I then use the estimated parameters to simulate annual expected welfare under different policies, including the first-best policy, the second-best policy and observed historical rates.

1.5.1 Wholesale market estimation

The data for demand are separated by zone, weatherzone, transmission firm, and type. I use a linear instrumental variable panel approach with fixed effects from zones, weatherzones, and transmission firms for each of the consumer types. The specific equation for quantity demanded by the average consumer of types i is

$$\begin{aligned} q_{i,l,z,k} = \beta_i + \beta_{i,p}(P_{z,k} + T_{il}) + \beta_{i,CDD} CDD_k \\ + \beta_{i,HDD} HDD_k + \epsilon_{i,k} \end{aligned} \tag{1.32}$$

where $q_{i,l,z,k}$ is the *average* consumption of consumer type i in place z under firm l. For estimation, price is instrumented by fuel prices for gas and

to the transmission network. Unmetered accounts are by definition unmetered; the payment for these meters are driven by backcasted weather models. I consider this constant demand profile to be normalized out—generators and retailers negotiate over demand that varies.

windspeed, and k represents one specific time period.[19] I use the parameter estimates to determine the change in demand with respect to the apparent price, $q'_{ilz} = \beta_{i,p}$.

For supply, I estimate by zone. I test a number of specifications, but settle on linear specification:

$$\begin{aligned} Q_{z,k} =& \beta_{z,s} + \beta_{z,p} P_{z,k} + \beta_{z,w} Windspeed_k \\ &+ \beta_{z,g} NaturalGas_k + +\nu_{z,k} \end{aligned} \tag{1.33}$$

with $P_{z,k}$ instrumented by demand shifters HDD and CDD by zone. Another specification, linear monthly aggregate, results can be seen in appendix B. I combine the estimation of supply and demand using a three-stage least squares procedure. For demand, I estimate these equations with pooled instrumental variables. This strategy works off the theoretical assumption that consumers of the same type in any area and under any transmission firm are indistinguishable from each other. In appendix B I include monthly fixed effects estimation results for robustness.

I restrict the time period of estimation by zone to 2007–2010. This allows me to focus on a consistent structure in the network; from 2004 – 2006 ERCOT operated an East zone that consisted of rural portions of the North and Houston zones. Using the 2007 – 2010 periods bypasses the structural change of inclusion of an East zone for generation behavior.

[19] Other fuel prices may be relevant, such as uranium and coal which serve as baseload. However, I don't find a statistically significant relationship between uranium, diesel, or coal and imputed market prices.

There are two different approaches to marginal cost. The first, which is akin to methods used by Puller [2007], Kahn et al. [1997], and Borenstein et al. [2002], uses imputed linear marginal costs derived from fuel costs, pollution permit costs, and engineering estimates of variable operating and maintenance costs. Market marginal costs are then the cost of supplying a single MWH from the next-most efficient supplier. I assume wind and hydroelectric marginal costs are zero.[20] The cost of provision from each generator is used with the linear inferred cost assumption applied to capacity of the generator. Nuclear plant output information is only available at the monthly data (via EIA), so I use the monthly value averaged by the number of observation periods in a month. For the amount of renewable (wind and hydro) generation used on average I use ERCOT values provided in their annual Market Reports.

The second approach is to assume generator market power in the market is negligible at the generator level (or $p_z = C'_g$). There are two reasons that this method would be suspect. The first, as shown in Borenstein et al. [2002], there can be periods where generators are able to influence the market price via induced congestion; this signifies market power even when generators with this ability have small relative capacities of production. Since I observe congestion in 10% of the data, this assumption may misspecify the model. The second reason is that this reduces the flexibility of the model to investigate impact to producer surplus. The advantage to this method is computational simplicity in estimating optimal second-best tariffs. In light of these weaknesses, I use

[20] This data can be found at http://www.ercot.com/calendar/2011/04/20110405-LTS

the first approach.

1.5.2 Transmission marginal costs

To recover transmission firm marginal costs, I estimate transmission firm variable O&M costs from quarterly data. I report results for an OLS specification, firm-specific specification, and a log-linear approach. In the structural simulation I use the firm-specific variable cost specification because the log-linear approach has a misspecified interpretation of the coefficient estimates compared to the linear approaches (however, I report the results as a robustness check of the estimation). In Appendix B other variable cost structures for transmission are considered.

I estimate transmission firm variable costs using the base specification

$$C_{k,l} = \beta_{1,l} q_{k,l} + \epsilon_{k,l} \tag{1.34}$$

summed over all intervals in a quarter k. No constant is included as this portion estimates specifically variable costs. The epsilon here represents unmeasurable heterogeneity between observations, which I assume to be iid mean 0. I do not have cost data on each k-interval of C_l, so instead I find the estimate of quarterly costs:

$$\sum_k C_{k,l} = \sum_k \beta_{1,l} q_{k,l} + \epsilon_{k,l} \tag{1.35}$$

The term $\epsilon_{k,l}$ I assume to be iid centered about zero with variance ς^2. Dividing equation 1.35 by K (is the total number of intervals k in a quarter—around

8,640 quarter-hours) gives

$$\frac{1}{K}\sum_k C_{k,l} = \beta_{1,l}\bar{q}_l + \frac{1}{K}\sum_k \epsilon_{k,l} \tag{1.36}$$

The variance of the averaged ϵ_l term is ς_l^2 since ϵ_l is iid. Equation 1.36 is the sample analogue to $\mathbb{E}(C_l(q_l)|q_l) = \beta_{1,l}q_l$.

I include no constant in the specification here since C is the *variable* cost of quantity transmission.

Marginal costs of transmission are the derivative of the outcome of this specification, or

$$\frac{\partial C}{\partial q} = \beta_{l,1} \tag{1.37}$$

In reporting the results of this estimation, I also include the results of a log-linear estimation for comparison purposes. However, a log-linear model ($\ln(costs) = \beta_{t,0} + \beta_{t,1}\ln(Q) + \epsilon$) does not allow for the coefficients to express the same interpretation as our quarterly average model in equation 1.36.

1.5.3 Simulation

The solution relationship described in equation 1.13 cannot be solved by a matrix inversion alone because equilibrium prices, marginal transmission costs, demand, and supply are a function of transmission rates. Using the parameter estimates of demand response, I use a fixed-point algorithm to maximize welfare subject to transmission firm budget constraints and nonnegative rates and quantities. Prices are solved directly from the parametric form assumptions

$$\underbrace{\beta_{z,p}P_z + X_s\delta_s + \nu_s}_{\text{Supply in zone } z} = \underbrace{\sum_m \sum_j \sigma_{jmz} \max\{0, \beta_{j,p}(P_z + T_{jm}) + X_j\delta_j\}}_{\text{Demand in zone } z} \tag{1.38}$$

where X_s and X_j are covariates and constant of supplier and j-type consumers, respectively, and δ_s and δ_j the coefficients on these respective covariates.

1.6 Results

In this section I report the results of the empirical strategy. First I review parameter estimates, then I report the results of the structural simulation.

1.6.1 Parameter estimates

Demand estimates used for average consumption by zone, weatherzone, transmission firm, and class type are found in table 1.7 (this average consumption corresponds to $q_i(P_z+T_{il})$ in the model). These estimates are pooled OLS and look at monthly average demand response to apparent price, a quadratic of temperature, and relative humidity. Apparent price (or the sum of price and transmission rate) are the coefficient on the demand response.

The linear demand model is consistent with inelasticity results common in the electricity demand literature. These coefficients give the average elasticities across all zones and firms found in table 1.8. The elasticities observed are within the support in comparison studies (where the time-frame may last

Table 1.7: Average hourly demand response, kWh

Consumer Type	$P_z + T_{jm}$	CDD	HDD	Constant
BUS	-.530†	.84†	.505†	43.9†
BUSIDR	-7.34†	4.26†	8.87†	1530.7†
BUSNO	-.0073†	.42†	.13†	1.8†
RES	-.082†	..64†	.31†	11.01†
	Supply shifters: natural gas price, windspeed †: 99% significance level, **: 95%, * 90%			

Table 1.8: Average Short- and Long-Term Demand Elasticity

Consumer Type	Short term Elasticity	Monthly Elasticity	Short-Term Comparison	Long-term Comparison
BUS	-0.0.38	-.28	-0.05	-.51*/-.147°
BUSIDR	-0.04	-.358	-0.05	-.8**
BUSNO	-0.0072	-.013	-0.05	-.51*/-.147°
RES	-0.024	-.148	-0.15	-.24°

Notes:
*: Annual, °: Quarterly
**: Some comparison studies separate out heavy industry from light industry.
A representative one from Lijesen [2007] is used here.
*** Monthly elasticity based on demand estimation reported in appendix B

from immediate response to a year). See Lijesen [2007] for a review of demand elasticities results.

Estimates of supply parameters are found in table 1.9. The four zones

Table 1.9: Hourly MWH Supply per Zone

Variable	Houston	North	South	West
P	499.0213†	214.07†	52.4324†	1.92199†
Gas	-3536.034†	-1427.451†	-359.12†	2.3539†
Windspeed	95.632†	8.9477†	11.2796†	3.5159†
Constant	12448.48†	3687.357†	2403.70†	487.249†

Notes:
Demand shifters: CDD, HDD
†: 99% significance level, **: 95%, * 90%

here are mostly consistent with what we would expect in regards to signs of the coefficients. Increased windspeed means increased wind production—implying higher quantity available. Increased gas cost results in increased costs to suppliers, hence we'd expect the supply to decrease. Price response is positive. Coefficients on the constant and magnitude of price response are decreasing in order of zone size.

There is one sign of potential model misspecification, however: the direction of the gas coefficient for the western zone is positive when we'd expect this to be negative. This may be a case of spurious correlation; in either case the value this is multiplied to is relatively small[21] and varies monthly in data, so the misspecification is relatively minor.

[21]Gas prices stay below 20 USD for the sample.

Table 1.10 reports cost estimates for each transmission firm using a number of specifications. The regressand used in the first through fourth specifications are firm cost. The log specification is included for comparison purposes only. As mentioned previously, the log specification has the wrong interpretation for the model; what is required is the coefficient estimates to be multiplied to the (arithmetic) average usage case.

For the simulation I use the firm-specific linear cost specification. This specification gives declining average total costs over the domain of usage for all five firms, and a constant marginal transmission cost for each firm.

1.6.2 Simulation Outcomes

This section reports the rate outcomes of the simulation. At present these numbers apply to an analysis of 2007 – 2010; as discussed before this allows me to bypass the 2003–2006 period with an additional overlapping zone. Table 1.11 reviews the rates that would be charged under the optimal second-best policy and actual cost-of-service policies.

The first noticeable pattern is that generally second-best rates are within the same range as cost-of-service counterparts. Second, virtually all consumers pay less under Ramsey-Boiteux tariffs than under the current rates, except for BUSIDR class customers.

The breakdown for these second-best uniform tariffs can be found in table 1.12, which contains the Lerner index, direct market effect, indirect market effect, and scaled inverse elasticity. The direct and indirect market effects can

Table 1.10: Transmission Costs Estimates

Variable	1	2	3	4	5	6	7	8
CP								
q	4.49†	4.47†	4.34†	4.32†				
$\ln(q)$					1.10†	.87†	1.07†	.701†
cons			1.06e+07†	1.14e+07†		4.68†		6.59†
TNMP								
q	4.49†	4.25†	4.34†	2.74†				
$\ln(q)$					1.10†	.872†	1.11†	.677†
cons			1.06e+07†	1.14e+07†		4.68†		6.59†
TCC								
q	4.49†	5.28†	4.34†	4.69†				
$\ln(q)$					1.10†	.872†	1.11†	.701†
cons			1.06e+07†	1.14e+07†		4.68†		6.59†
TNC								
q	4.49†	5.91†	4.34†	3.95†				
$\ln(q)$					1.10†	.872†	1.13†	.691†
cons			1.06e+07†	1.14e+07†		4.68†		6.59†
TXU								
q	4.49†	4.45	4.34†	4.32†				
$\ln(q)$			1.10†	.872†			1.09†	.691†
cons			1.06e+07†	1.14e+07†		4.68†		6.59†
N	153	153	153	153	153	153	153	153
R^2	.9054	.9066	.8429	.8438	.9990	.9029	.9993	.9148

Notes:
1: Cost
2: Firm-Specific Cost
3: Cost with Constant
4: Firm-Specific Cost with Constant
5: Log
6: Log with Constant
7: Firm-Specific Log
8: Firm-Specific Log with Constant
†: 99% significance level, **: 95%, *: 90%
(5) and (7) exhibit autocorrelation

Table 1.11: MWH Transmission Rate Comparison by Transmission Firm

Market Participant	First-Best	Second-Best	Cost of Service	Counts
CP BUS	4.47	9.47	18.49	113,376
CP BUSIDR	4.47	27.51	18.75	3,482
CP BUSNO	4.47	9.64	21.21	124,119
CP RES	4.47	4.80	23.66	17,922,09
TCC BUS	5.28	11.00	18.49	79,139
TCC BUSIDR	5.28	31.27	16.96	608
TCC BUSNO	5.28	10.44	21.29	26,621
TCC RES	5.28	6.41	19.92	643,205
TNC BUS	5.91	11.15	10.12	21,246
TNC BUSIDR	5.91	21.94	16.96	342
TNC BUSNO	5.91	10.82	34.46	17,700
TNC RES	5.91	7.07	25.23	144,029
TNMP BUS	4.25	10.02	30.87	19,795
TNMP BUSIDR	4.25	27.31	32.18	183
TNMP BUSNO	4.25	9.43	37.21	12,883
TNMP RES	4.25	4.53	22.08	183,676
TXU BUS	4.45	10.67	20.66	186,730
TXU BUSIDR	4.45	29.11	20.06	5,414
TXU BUSNO	4.45	9.26	22.37	209,508
TXU RES	4.45	4.61	19.12	2,611,371
All values statistically significant at least at 95% level				

be seen as the dollar impact a tariff change has on the market. The first observation is that the direct market effect is fairly large for all consumer types: this is a scaling that a tariff change has on generator markup. Also, the indirect impact is quite small. The second observation is that the percentage markup on each type is fairly large—ranging from 15% to 90%; yet each markup is roughly within the same range as markups under the same transmission firm.

Table 1.12: Unweighted Second-Best Direct, Indirect, and Other Revenue Market Effects by Transmission Firm by MWH

Market Participant	Lerner Index	Direct Effect	Indirect Effect	Scaled Inverse elasticity
CP BUS	0.53	-62.11	5.8	0.52
CP BUSIDR	0.84	-57.53	2.04	0.44
CP BUSNO	0.48	-57.24	6.52	0.49
CP RES	0.07	-179.96	6.69	1.71
TCC BUS	0.52	-81.88	2.13	1.25
TCC BUSIDR	0.83	-69.65	0.78	1.61
TCC BUSNO	0.49	-69.43	2.33	1.02
TCC RES	0.18	-202.52	3.63	1.37
TNC BUS	0.47	-77.55	2.48	1.52
TNC BUSIDR	0.73	-71.52	1.28	2.27
TNC BUSNO	0.45	-71.35	2.59	1.06
TNC RES	0.16	-100.93	3.96	1.15
TNMP BUS	0.58	-65.34	4.87	0.55
TNMP BUSIDR	0.84	-63.89	1.75	0.59
TNMP BUSNO	0.55	-64.56	5.13	0.5
TNMP RES	0.06	-65.38	10.24	0.59
TXU BUS	0.58	-78.13	2.58	1.38
TXU BUSIDR	0.85	-71.15	0.96	1.53
TXU BUSNO	0.52	-70.72	3.06	1.17
TXU RES	0.03	-262.56	5.62	2.62

1.6.3 Social Welfare under Optimal Policy and Alternatives

Table 1.13 shows the welfare under a first-best, second-best, and cost-of-service policy. Consumer welfare under the second-best policy fares worse overall than under the cost-of-service policy. In absolute terms, net consumer welfare decreases by roughly 5% overall due to increases in prices (see table 1.14). Relative to the cost-of-service rate, the second-best rate reclaims roughly 74% of the deadweight loss in the market between net consumer sur-

Table 1.13: Average Quarterly-Hour Welfare Breakdown In Thousands USD

Firm/Type	FB	SB	COS	SB-COS	% SB/FB	COS/FB
CP BUS	170.7	136.2	185.4	-49.2	79.8%	108.6%
CP BUSIDR	151.7	98.1	154.4	-56.3	64.7%	101.8%
CP BUSNO	5.4	4.4	5	-0.6	81.5%	92.6%
CP RES	353.7	375	224.1	150.9	106%	63.4%
TCC BUS	38.1	25.7	39.9	-14.2	67.5%	104.7%
TCC BUSIDR	20.8	12	21.7	-9.7	57.7%	104.3%
TCC BUSNO	0.4	0.3	0.3	0	75%	75%
TCC RES	5.8	7.8	3.7	4.1	134.5%	63.8%
TNC BUS	17.7	13.7	33.4	-19.7	77.4%	188.7%
TNC BUSIDR	10.4	7.5	11.3	-3.8	72.1%	108.7%
TNC BUSNO	0.3	0.2	0.1	0.1	66.7%	33.3%
TNC RES	1.1	1.5	0.1	1.4	136.4%	9.1%
TNMP BUS	22.9	17.1	9.9	7.2	74.7%	43.2%
TNMP BUSIDR	7	4.5	5.4	-0.9	64.3%	77.1%
TNMP BUSNO	0.4	0.3	0.1	0.2	75%	25%
TNMP RES	21.1	22.9	15.2	7.7	108.5%	72%
TXU BUS	145.3	97.5	124.2	-26.7	67.1%	85.5%
TXU BUSIDR	178.7	103.6	173.3	-69.7	58%	97%
TXU BUSNO	3.6	2.5	2.5	0	69.4%	69.4%
TXU RES	29.4	43.9	22.8	21.1	149.3%	77.6%
CS Subtotal	1184.3	974.7	1032.6	-57.9	82.3%	87.2%
H	2778.9	2731.7	2031.7	700	98.3%	73.1%
S	440.3	427.7	352	75.7	97.1%	79.9%
W	358.5	351.3	302.5	48.8	98%	84.4%
N	1434.7	1408.5	1108.5	300	98.2%	77.3%
Profits	2,822	2,748.7	1,890.2	858.5	97.4%	67%
Annual Profits	24,721*	24,079*	16,558*	7,521*	97.4%	67%
All net consumer surplus values averaged by customer counts in table 1.11						
*: millions USD						

plus and the efficiency of the COS rule. Under a first best policy, consumer surplus increases by 1.3 billion USD, and when netted of fixed fees a 833 mllion

Table 1.14: Average Quarterly-Hour Simulation Outcomes In Thousands USD

Participant/Area	FB	SB	COS	SB-COS	% SB/FB	COS/FB
CP	-22.38	0	6.3			
TCC	-9.45	0	5.4			
TNC	-3.19	0	-0.9			
TNMP	-3.32	0	2.5			
TXU	-40.04	0	20.2			
H	53.54	49.92	33.10			
N	58.11	54.71	42.06			
S	57.53	52.40	46.51			
W	59.33	56.82	47.63			
Net Welfare	3,950	3,723	2,922	801	94.5%	74.5%
Gross Welfare	4,006	3,723	2,922	801	92.9%	73.0 %
Annual Net	34,600*	32,617*	25,782*	6,835*	94.5%	74.5 %
Annual Gross	35,096*	32,617*	25,782*	6,835*	92.9%	73.0%
*: millions USD						

USD increase is realized.[22]

Producer surplus (generator profits) fare well. Generators receive 30% more revenue under the second-best Ramsey pricing rule. The specific amount of annual welfare under a first-best policy increase would cover 56.2% of generation subsidies paid for by the state of Texas and the US government in 2006 (roughly 13 billion USD). Under a second-best policy producer surplus would cover 52.2% of total generation subsidies.

Under the first-best policy, firms require a transfer. Under a cost-of-service policy all transmission firms except TNC turn a profit. Transfers under

[22]The political economy question of from which groups to collect the fixed fee is out of the scope of this paper. Net values reported reflect collection directly from gross welfare.

a COS regime is distinct from a FB regime. In the first-best case, a transfer is handled through a fixed fee proportioned to consumers. If transmission firms in a cost-of-service situation required a transfer, this transfer cannot be charged to consumers; this amount would need to be raised through outside sources such as taxes or government financing.

1.7 Conclusions

Many electricity markets have restructured while retaining legacy pricing policies. These policies employ cost-of-service regulation that generally ignore economic factors. Ignoring these effects causes large distortions on consumption and production decisions in electricity.

In Texas, the Public Utility Commission uses a modified cost-of-service rate that charges a tariff to cover total transmission costs. The modification uses as average costs the total cost divided by a measure of the maximum quantity during an observed market period, then adjusts this in an ad-hoc manner year to year. In addition to economic distortions caused by cost-of-service policies, this introduces additional distortions by over-emphasizing the impact of the maximum system demand, ignoring demand elasticities among consumer types, and the impact of regulating on firm's consumers has on other firms and consumers.

In this paper I model these interactions and show the relative winners and losers under each of the policies. Compared to the cost-of-service rate, a second-best Ramsey pricing rule would alleviate up to 74% of dead-weight loss and mostly cover currently implemented generation subsidies. However, this would come at the expense of some transmission firms earning lower profits and some customer types cross-subsidizing other types under the same transmission company.

Further work to expand the precision of this project would include employing a more expansive variable transmission costs dataset that incorporates physical infrastructure topology. Also, further work is needed to determine how transmission tariffs affect generation bidding decisions in the residual demand spot market. Finally, an extension incorporating endogenous network transmission expansion (and the impact to consumer welfare and generator market power) is essential for expansive policy evaluation.

Chapter 2

Dynamic Platform Investment in Two-Sided Markets: The Impact of Network Neutrality

2.1 Introduction

In 2006, the issue of network neutrality took hold in the public discourse in the United States. On one end of the political debate stood telecommunications and broadband providers like Verizon, AT&T, and Comcast; the other side consisted of individual bloggers, internet heavyweights such as Google, and Open Internet advocates. At the heart of the issue was the concept of "network neutrality," which essentially means that network services providers cannot discriminate against bits traveling across their networks (except in cases of illegal activity).

Before a 2006 Congressional hearing on the subject, network service providers (ISPs) testified to occasionally exercising various forms of discrimination under the auspices of "network management" (e.g. congestion resolution and content filtering). Applications used for both legitimate and illegitimate uses were blocked, such as BitTorrent and file-sharing protocols sharing recent television content as well as legitimate content like versions of the Bible. At the time, ISPs were beginning to assert rights of filtering and billing not previously considered. *Businessweek* quoted Ed Whitacre, AT&T's then-CEO and board chair, regarding network operation:

> Now what they [content providers] would like to do is use my pipes free, but I ain't going to let them do that because we have spent this capital and we have to have a return on it. So there's going to have to be some mechanism for these people who use these pipes to pay for the portion they're using. Why should they be allowed to use my pipes? [1]

In effect, Mr. Whitacre promised to implement two-sided pricing on last-mile access for broadband (through classification as information providers–something dial-up services were not allowed to do as telecommunication providers).

The fear of Open Internet advocates is that, with the permission and the right to discriminate content, ISPs would charge content producers to push data through a faster network channel; those content providers choosing to not pay would have their content relegated to slower channel. In the minds of net neutrality supporters, this is equivalent to extortion [United States House of Representatives, 2006]. Further, there is fear among advocates that legally produced and distributed content will be blocked in order for the ISPs to give preferential treatment to ISP-owned media (especially on-demand video, as in the cases of Comcast and Time-Warner).

[1]Source: http://www.businessweek.com/magazine/content/05_45/b3958092.htm

Until early 2014 the issue had remained mostly settled, but then a legal case reopened concerns regarding the legal and economic impacts of network neutrality legislation. For a time, the FCC implemented a list of net neutrality rules with H.R. 5353. These rules, as implemented until 2014[2], include

- Purpose: The purpose of (the FCC-released rules) is to preserve the Internet as an open platform enabling consumer choice, freedom of expression, end-user control, competition, and the freedom to innovate without permission.

- Transparency: A person engaged in the provision of broadband Internet access service shall publicly disclose accurate information regarding the network management practices, performance, and commercial terms of its broadband Internet access services sufficient for consumers to make informed choices regarding use of such services and for content, application, service, and device providers to develop, market, and maintain Internet offerings.

- No Blocking: A person engaged in the provision of fixed broadband Internet access service, insofar as such person is so engaged, shall not block lawful content, applications, services, or non-harmful devices, subject to

[2]These rules were declared out of the domain of the FCC to enforce since ISPs were not identified as "common carriers" on January 14, 2014 in **Verizon Communications Inc. v. Federal Communications Commission (2014)** by the DC Circuit Court. In the short time from then until this writing numerous allegations against ISPs have been levied regarding non-neutral behavior.

reasonable network management. A person engaged in the provision of mobile broadband Internet access service, insofar as such person is so engaged, shall not block consumers from accessing lawful websites, subject to reasonable network management; nor shall such person block applications that compete with the provider's voice or video telephony services, subject to reasonable network management

- No Unreasonable Discrimination: A person engaged in the provision of fixed broadband Internet access service, insofar as such person is so engaged, shall not unreasonably discriminate in transmitting lawful network traffic over a consumer's broadband Internet access service. Reasonable network management shall not constitute unreasonable discrimination.

The FCC tentatively has legal authority to implement principle-based rules regarding U.S. network management practices; the application of this authority was curtailed in January 2014, as noted earlier.

This paper develops a framework for dynamic platforms to investigate the claim made by ISP providers that under network neutrality rules forbidding ISPs charging content providers, the ability of ISP providers to innovate would be significantly curtailed. Specifically, I answer the following question: what are the the dynamic network investment decisions of ISPs under both neutral and non-neutral network regimes? For the purposes of this paper, I focus specifically on video content providers such as Netflix, Amazon, Hulu, and

Vimeo; the reasoning for this decision is, as of 2011, online video accounts for more than forty-five percent of all US network traffic. [3] The specific aspect of network neutrality I investigate directly answers the challenge expressed by Mr. Whitacre (and others with similar claims) from congressional hearings [United States House of Representatives, 2008, 2006, see], which is that an ISP can charge a content provider for content delivery.

Although much has been published on the legal framework and issues surrounding network neutrality, little focus has been given to economic impact or optimal policies. Economides and Tåg [2012] and Choi and Kim [2010] are both seminal works on this subject. Choi and Kim [2010] analyzes the dynamic implications of net neutrality rules to ISPs and content providers (CPs) welfare, and find that, contrary to the claims of ISPs, that net neutrality may allow for increased ISP profits; these results, however, are ambiguous contingent on parameterization. Further, as they note in their conclusion, a two-sided market analysis is needed to analyze what happens when CPs can charge the end-user. Economides and Tåg [2012] use a two-sided market analysis to investigate the economic consequences for CPs and ISPs given non-neutral network policy. Their main point of research is in *two-sided pricing*, where the ISP charges both end-users (in a contract with the ISP) and CPs with whom there is no contractual relationship. The authors find that with a static framework under reasonable parameterizations, societal welfare is maximized by having ISPs pay CPs for production; under no situation do the authors find that a

[3] Source (accessed 1 July 2011): http://www.sandvine.com/news/global_broadband_trends.asp

positive fee to CPs desirable for welfare purposes.

Other related works involving net neutrality include Cheng et al. [2011], which finds neutral network regime benefits IPS and harms CPs; and Hermalin and Katz [2007] which finds on total surplus is reduced (but low valuation CPs are excluded). In order to address the dynamics of the ISP/CP two-sided market, I modify the Ericson and Pakes [1995] algorithm for use with a two-sided market–namely the ISP platform, and the video industry for online video delivery (such as Netflix streaming, Youtube, Vimeo, Amazon, and Vevo). This represents a first attempt to implement dynamic two-sided market analysis to the network neutrality issue.

Recent theoretical work on two-sided markets includes Rochet and Tirole [2002], Rochet and Tirole [2006], Choi [2010], and Eisenmann et al. [2011]. The current literature focuses on static, utility-maximizing decisions under various competition assumptions by firms, platform service providers, and households. Two notable counterexamples which buck this trend are Lee [2013], a dynamic empirical paper using the Berry et al. [1995] method for demand estimation, which looks at platform competition in a durable goods industry (video game platforms 2000–2006); and Choi and Kim [2010], which looks at network neutrality. Perhaps because of the complexity of the topic, the literature for two-sided markets is light on the dynamic side.[4]

[4]The question this paper addresses requires a dynamic model to address platform investment; thus it builds onto the dynamic two-sided market literature.

2.2 Model

In order to compute the dynamics of a two-sided market, I employ a modified version of Ericson and Pakes [1995]. I use a model of the ISP/CP/consumer two-sided market that incorporates charges to both sides of the market. I focus on an average revenue per GB delivered consumption model. Network neutrality is modeled as a platform that cannot charge a firm for content distribution; only the user side may be charged. A non-neutral network would thus face no such constraint. This is a little different from the typical definition of network neutrality in that all content delivered is assumed equal. However, the charge from Mr. Whitacre and others is that the inability to charge firms for content delivered will stifle innovation. Thus, the implementation of network neutrality is assumed to be in a very lax regulatory environment where platforms can discriminate content charges for the user side of the market, *not* the firm side. This fits well with the "reasonable network management" exception provided under FCC rules.[5]

The Ericson-Pakes algorithm requires that the type of static market the

[5] In this case, the charge to both sides of the market behaves similar to an excise tax to both sides. This is a desirable property for the following reasons:

- Both firms and the platform making decisions have restricted information sets. Fixed costs may be unknown to other market entities. Industry reports typically report average costs, but not fixed costs. While one could argue that consumer subscription fees are well known, the profits seen later in the model are not coming from ISP subscriptions by consumers, but by usage fees paid by consumers–a very different animal.
- The computational complexity of the model is significantly reduced.

dynamic market is based on be fully specified. I first explain this specification, and then move to the dynamics of the model. I then explain the equilibrium used in the algorithm.

2.2.1 Static Content Producer Profit Maximization

For the static profit maximization portion of the model, I use a specification similar to Pakes, et al. (1993). A platform chooses a_f, a_b to maximize profits, where a_f is the per-interaction fee the the platform charges the firm, and a_b is the per-interaction percentage the platform charges the consumer. Average demand in the industry is specified as gigabytes of data consumption using the formula

$$P(Q) = \frac{\alpha + \beta \ln Q}{1 + a_b} \tag{2.1}$$

where $\beta < 0$. $P(Q)$ corresponds to empirical findings from Nevo et al. [2013].

Content providers compete in Cournot competition, taking a_f and a_b as given. They produce the same good and are differentiated by marginal costs $c_i = \gamma_1 \mathrm{e}^{-\gamma_2 \omega_i}$. For the ith firm, the profit function is

$$\pi(q_i; \omega_i, s, a_f, a_b) = [(1 - a_f)P(Q)q_i - c_i q_i] - f \tag{2.2}$$

where a_f is per-unit percentage of revenue the firm pays to the platform, $P(Q)$ is the market price, f is the fixed cost of operation.

By differentiation, the first order equilibrium conditions $\frac{\partial \pi_i}{\partial q_i}$ are

$$\frac{\partial \pi_i}{\partial q_i} = \frac{1 - a_f}{1 + a_b} \left[\alpha + \beta \ln \sum_j q_j + \frac{\beta q_i}{\sum_j q_j} \right] - c_i = 0 \tag{2.3}$$

The platform receives profits per each sale of

$$\pi^p(a_f, a_b) = [(a_b + a_f)P - c_p]Q \tag{2.4}$$

where c_p is the cost per transaction. One can readily see that the profits the platform receives is non-neutral to different specifications of a, the total fee per interaction, as the market equilibrium is affected nonlinearly. This is proposed by Rochet and Tirole [2006] as a necessary condition for a two-sided market.

This static model can be extended to multiple industries relying on the same platform. For model simplicity, I assume the platform exhibits neither economies nor diseconomies of scope within other industries: the end result is that profits are additive across industries engaging in the platform, and we can focus on one industry without additional complexity in notation and without loss of (much) generality.

2.2.2 Dynamic Model

Common knowledge to all agents at each time period is the *state of the market* $s_t \in \mathbb{Z}_+^\infty$, which is a listing of the efficiency level ω_{it} for all i at time t. s_t is a sequence of whole numbers, where each integer in the nth position represents the number of firms with the nth efficiency level (i.e. number of firms with the same ω_{it} marginal costs from the static problem, $c_i = \gamma_1 \mathrm{e}^{-\gamma_2 \omega_{it}}$).

2.2.2.1 Actors

The dynamic portion of a two-sided market involves four types of actors: internet service providers (platforms), incumbent content providers, entrants, and consumers.

Platform service providers (or, for short, platforms) facilitate exchange between different portions of the market where it would be overly costly to trade without the platform. For the purposes of this paper, I assume that the market could not exist without the assistance of the platform. I also assume no multihoming, so that the consumers and producers cannot switch between different service providers.[6] Thus, platforms receive net profit $(a_f + a_b)P_t - c_p$ for each interaction at time t, where c_p is the marginal platform cost per interaction.. The dynamic decision of the platform lies in its current-period investment strategy. The platform can invest in the quality of its service for the firm side of the market: higher investment results in a larger potential for a better state for incumbents and entrants in the next period. Once a platform chooses fees a_f and a_b in time 0 it is locked into this technology investment regime. Thus, the action set available to the platform is to maximize expected profits through setting appropriate firm and user fees a_f and a_b. [7]

Static profits for the platform may well be negative under the parameterization. I do not correct this and force the firm to invest at some minimum level for two reasons: the first reason is that the industry considered (online video) is only one industry for which the ISP serves as a platform; video con-

[6] In the US often the local broadband market is a monopoly or, less commonly, a duopoly with a dominant player.

[7] While allowing the platform to create a new rate schedule each month would be ideal, the time period of the model is in months. Contracts with broadband ISPs are usually in yearly or even multi-year periods. I have the ISP choose initial contract terms offered to maintain simplicity.

tent delivery is not the only source of revenue of the ISP (this allows for other ISP-served industries to have higher profits, a point which is not considered in this model); the second reason is that, although platform profits may be negative, the expected discounted future valuation of investment in this period may be quite large given higher future industry profits. In addition, the concept of R&D in the model is broad: it can also be considered a network maintenance cost. Hence, the platform always invests some percentage of its revenue.

The platform's problem is, given market state s, previously set user fee a_b and firm fee a_f,

$$V^p(s, a_f, a_b) = \max_{y \in \not\succ} \{((a_f + a_b)P(1-y) - c_p)\, Q + \beta \mathrm{E}(V^p(s'|s,y)|y)\} \quad (2.5)$$

where y is the percentage level of investment (of current period profits), and c_p is the marginal cost of delivery. P and Q are from the firms' side of the market the platform serves.

All content providers which, for a given time period t, were engaged within the platform service for time period $t-1$ as either an incumbent or an entrant, solves the incumbent's problem. Each firm knows its efficiency level ω_{it} and the state of the market s_t. At each period in time, a firm can choose to exit and receive stationary scrap value ϕ, or to engage in competition. Should the firm choose to compete, its dynamic choice is investment level x, which in part determines the firm's efficiency level at time $t+1$. Should the firm choose to exit the market, it exits all future time periods.

There is a common marginal cost to investment across all firms, denoted μ, and common discount factor β. Thus, the incumbent firm solves

$$V(\omega, s, a_f, a_b) = \max \left[\sup_{x \geq 0} \left\{ \pi(q_i; \omega_i, s, a_f, a_b) - \mu x + \beta \mathrm{E} \left(V | x, a_f, a_b \right) \right\}, \phi \right]. \tag{2.6}$$

At this point I do not specify the Markov process the incumbent firm faces; I detail this in section 2.2.2.4.

Entering content providers must choose between entering the market or receiving the outside option of 0. Each firm that enters faces entry cost x_e^m, which is nondecreasing in the number of entrants m. The action space of the entrant is to enter or to stay out. Entering firms observe the state of the market s_t, platform investment level y, user fee a_b, and firm fee a_f.

The value of entering the market for the entrant at time t is denoted $V^e(s_t, m_{t+1}, a_f, a_b)$, where m_{t+1} denotes the number of entrants that will engage in the market in time $t+1$.

Hence, the entrants problem is to solve

$$V^e(s_t, m_{t+1}, a_f, a_b) = \max \left\{ 0, -x_e^m + \beta \mathrm{E}_\omega \left[V(\omega, s, a_f, a_b, y) \right] \right\} \tag{2.7}$$

After entrants make their decision, time increments, From then, entrants are treated identically to incumbents: they receive an efficiency draw and make decisions at the same time as an incumbent. Thus, it is feasible that a firm chooses to enter, receives an efficiency draw wherein they would choose to exit, and do so. This would earn such entrant a payoff of $-x_e^m + \beta\phi$. To rule this out, I ensure the parameterization is such that $x_e^m > \beta\phi$. A discussion on how the number of entering firms is determined is found in section 2.2.2.3.

The potential efficiency level of an entrant is contained in the set $\Omega^e \subset \mathbb{Z}$. For the purposes of this paper, I do not explicitly define this set, but point out that it is well explained in previous literature (see Ericson & Pakes (1995)). To provide a concrete example, I set $\Omega_e = \{2\}$ later in the simulation.

Consumer demand is modeled based off Nevo et al. [2013]. In line with work by Ericson & Pakes (1995), each firm knows something about the state of the market and the inverse demand curve, which I model as $P(Q) = \frac{\alpha+\beta\ln(Q)}{1+a_b}$.[8]

2.2.2.2 Timing

The timing of the model is as follows:

1. At time $t = 0$, the platform sets per-interaction fees a_f and a_b.

2. Potential entrants choose to enter based on a_f, a_b, and the current level of y, and the previous time period's state of the market s_{t-1} (Note: s_0 is given as an initial condition, but this will be described later)

[8] Perhaps this may be seen as overly restrictive. As with the lack of membership fees, consider the information set of both firms and platform as knowing only a little about the demand of the market: they know enough to observe average demand for their product, and to base estimates on said average.

3. Time increments by one period

4. Firms draw new efficiency levels, then choose to exit or to produce

5. Platform observes the state of the market s, and determines level of investment, which positively impacts firm's future expectations

6. Firms compete according to the static model above, and choose investment level x_i, which positively influences the next period's efficiency draw

7. Cycle returns to step 2

2.2.2.3 Laws of Motion and Dynamics: Entrant

At this point I discuss how the number of entrants are determined for a given period. Previously, m_{t+1} was defined as the number of firms (entrants and incumbents) at time t who will participate in the market at time $t+1$. How this number is determined is clarified at this point.

Suppose there are countably infinite *ex ante* identical firms whom desire to enter the market at each period. Each potential entrant receives a decision draw without replacement from $\mathbb{N}$. The first firm decides whether to enter or stay out given current market conditions. Then the second decides, and so forth. The best response for the nth firm in this situation is to observe whether the $(n-1)$th firm chose to enter; if no, then no enter. If yes, then the nth firm determines whether to enter based on $V^e(s_t, n-1, a_f, a_b)$. If 0 is the option chosen, all firms following n will also choose to not enter. Otherwise, the process continues. This conceptually solves the simultaneity problem of entrants.

We then see that m is a function of state variables s, a_f, a_b, and y. This motivates the definition of $m(s, y)$ as

$$m(s, a_f, a_b, y) \equiv \begin{cases} 0 \qquad \text{if } V^e(s, m, a_f, a_b, y) < x_e^m \text{ for all } m \geq 1 \\ \min\big\{m \in \mathbb{Z}_+ \mid \big[V^e(s, m, a_f, a_b, y) > x_e^m\big] \\ \cap\big[V^e(s, m+1, a_f, a_b, y) < x_e^{m+1}\big]\big\} \quad \text{otherwise} \end{cases}$$

There is no reason x_e^m needs to be deterministic. Indeed, this could be considered a random variable, and will be assumed as such in the simulation.

2.2.2.4 Laws of Motion and Dynamics: Incumbent

There are a number of random variables associated with the efficiency level of the firm. The first random variable to consider is $\eta \sim H(y)$, which is related to the value of the outside option for consumers (or an erosion of consumer utility from consuming the produced good). Alternatively, Ericson & Pakes see η as an increase in factor input price. In this paper, η effects firms' future expected profits through the value of the platform. η is contained in the set $\{-k_1, -k_1 + 1, \ldots, 0\}$ for some whole number k_1. η is common to all firms within the industry.The distribution of η becomes skewed positively by platform investment.

The second random variable is $\tau \sim T(x)$, which represents the increase in firm efficiency–thus, τ is idiosyncratic to each firm. Similar to η, $\tau \in \{0, 1, \ldots, k_2\}$ for some whole number k_2. The distribution of τ is "increasing" in x, in that if $x' > x$ then $T(x')$ first-order stochastically dominates $T(x)$. One could consider τ as the increase in efficiency due to research and development.

The firm's next period efficiency level (conditional on x) is denoted $\omega'_i = \tau_i + \eta + \omega_i$. Hence, ω' is distributed by a convolution of the distributions for τ and η. Note that the state of the market does not directly impact the dynamic decisions and state variables, but do influence the policy decisions $x(\omega, s)$, and $\chi(\omega, s)$ (where $\chi(\cdot)$ is the binary market participation decision).

2.2.3 Equilibrium

My model uses an extension of the well-known Markov-Perfect Nash equilibrium (MPE, originally defined by Maskin and Tirole [1988a] and Maskin and Tirole [1988b], but adapted by Ericson and Pakes [1995]). For a given $\{a_f, a_b, y\}$, the definition follows Ericson-Pakes explicitly (hence, each subgame is an MPE in its own right). The final equilibrium then depends explicitly on the platform's choice of investment y.

Similar to Ericson and Pakes [1995], the equilibrium for this model is a eight-tuple defined as

$$\Big\{V(\omega, s, a_f, a_b, y), x(\omega, s, a_f, a_b, y), \chi(\omega, s, a_f, a_b, y), Q(s'|s, y),$$
$$m(s, a_f, a_b, y), a_b, a_f, y\Big\}_{(\omega,s)\in\Omega\times\mathbb{Z},s^0,a_f\in[0,1],a_b\geq 0,y\in\Upsilon} \tag{2.8}$$

where $\Omega = (0, \ldots, K)$, $K < \infty$, such that

1. For every (ω, s, y), $V(\omega, s, a_f, a_b, y)$ solves the incumbent firm's problem

2. For every (ω, s, y), $x(\omega, s, a_f, a_b, y)$, $\chi_I(\omega, s, a_f, a_b, y)$, and $\chi_E(s, a_f, a_b, y)$ solve the incumbent's and entrant's problem

3. Laws of motion are consistent (see Ericson & Pakes for a more formal treatment)

4. $m(s, a_f, a_b, y)$ consistently determines the number of entrants

5. There is an exogenously given state s^0

6. a_f, a_b, y solve the platform's problem given s

This equilibrium is not necessarily unique.[9]

2.3 Simulation and Parameterization

To simulate my model, I follow Pakes and McGuire [2001] with a calibration based on the ISP and CP industries. All parameters are in per-consumer per-month units (e.g. marginal cost is dollars per consumer per month). Based on the simulation results, we can determine if dynamic investment decisions by platforms will change due to network neutrality legislation. The simulation runs 1000 times per initial state (a_f, a_b, s^0, y) for a time horizon of $t \in \{0, \ldots, 100\}$. Finally, the simulation reports the average simulated

[9] As a technical point, the code used later in the simulation rejects any equilibrium such that firms at lower efficiency levels choose to stay in the market when higher efficiency firms choose to exit. This is discussed in detail in Pakes and McGuire [2001].

surpluses, profits, number of firms, deviation from initial investment choice, and instability of investment choice of the platform.[10]

Data covering the necessary parameters is scant in most cases and nonexistent for the rest. Because of this, the calibration is taken mainly from industry reports and engineering estimates of the online video delivery and the US Internet service provider industries.[11]

For the distribution of η, the continuing usefulness of the platform to firms, I use $\eta \in \{-1, 0\}$. Hence, we have that $\Pr(\eta = -1|y) = \delta(y) = \frac{1}{1+gy}$ and $\Pr(\eta = 0) = 1 - \delta(y) = \frac{gy}{1+gy}$. For τ, I use $\tau \in \{0, 1\}$, and for $T(x)$ I use $\Pr(\tau = 1|x) = \frac{dx}{1+dx}$ and $\Pr(\tau = 0|x) = \frac{1}{1+dx}$. Thus, $\Pr(\omega' = \omega|x, y) = (1 - \delta(y)) \cdot \frac{1}{1+dx} + \delta(y) \cdot \frac{dx}{1+dx}$, $\Pr(\omega' = \omega + 1|x, y) = (1 - \delta(y)) \cdot \frac{dx}{1+dx}$, and $\Pr(\omega' = \omega - 1|x) = \delta(y) \cdot \frac{1}{1+dx}$.

For entering firms, I assume a uniform distribution of entry fees over $[X_{EL}, X_{EH}] = [.05, .1]$. Entering firms have the same random entry cost when $N = 0, 1, 2$ and ∞ when $N \geq 3$. Recall that these values are per initial user per month usage. Initial firm efficiency levels are $\omega \in \Omega_e$; I use $\Omega_e = \{3\}$, which is pulled from the marginal cost of operating a video delivery service where the hosting is outsourced (a common during the startup period of a technical

[10] Average instability of investment choice is, given a_f, a_b, s, and the incoming level of platform investment, how likely is it the platform changes its investment strategy from period to period).

[11] CP Sources: comScore, Grabstat, hackingnetflix, feedflix. ISP Sources: dslreports, Pereira and Ribeiro [2011]. Note that the per-user per-month estimate of platform marginal costs is based on "worst-case scenario" pricing, as reported by dslreports.

business).[12] Thus x_e^m is nondecreasing in m, and the model requirements for this are satisfied. The estimated cost to the ISP of gigabyte per hour consumption is determined from dslreports, and from comScore the average number of minutes of video content watched per month and average video quality are determined. From hackingnetflix, the number of Netflix subscribers are reported, as well as estimated loss in number of subscribers due to the very recent price change (early July 2011). From these reports the average per-user per-month costs are ascertained for both content providers and platforms. Further from these reports, US Fed data on GDP growth change, and SEC filings for public ISPs and CPs, one can determine the parameters needed for the probability density functions τ and η.

The algorithm requires an exogenous decision of the maximum number of firms N which can be engaged in the industry (the increase in time is roughly $O(N^N)$). I use a maximum of 3 firms, since under the ISP/CP parameterization the simulation rarely achieved more firms (e.g. 4,5) when allowed. This affects the ability of entrants to enter within the algorithm: if $m < N$, entrance to the market is possible. This is clearly a limiting factor on the model; however, using the parameterization detailed here, allowing $N > 4$ resulted in exactly two time periods in one observation where the 4 firm limit was reported to hit. Another way to consider this restriction is as a consequence of $x_e^m = \infty$ for all $m \geq 4$.

[12] This value, for the interested reader, is 0.077 per GB per hour. The entry fee distribution is over the range of costs for video hosting

For the simulation, I have three loops over the algorithm for user fees, firm fees, and the elements of Υ. I set user fees $a_b \in \{0, \frac{1}{10}, \frac{2}{10}, \frac{3}{10}, \ldots, \frac{9}{10}\}$ and $a_f \in \{0, \frac{1}{20}, \frac{2}{20}, \ldots \frac{16}{20}\}$. The firm fee is not extended to 1 since this would result trivially in no firms entering–at $a_f = .7$ the platform charges 70% of firm revenue. The user fee could conceivably be much higher than 100%, however results from this portion of the domain did not result in compelling results.

I set the highest attainable efficiency level to be 12 after observing no firms in each subgame equilibrium chose to invest to achieve this level. Platform research and development levels I set to be $\{0.05, 0.20\}$ based on averaged R&D investment levels in public ISP SEC filings corresponding to "good" and "bad" years for the content delivery service the following year.

Finally, I set the content provider scrap value $\phi = 0.5$ and fixed fee $f = 1$. For *phi* this makes intuitive sense in that this represents a low value for selling all equipment, legal rights to content, etc. at an average of \$.50 per user. I choose $f = 1$ due to lack of data–the total costs of per-capita operation are described above. This total cost includes per-capita fixed costs, but the reports I have seen do not itemize the costs.

In order for the Ericson-Pakes algorithm to achieve MPE in each subgame, a few assumptions must be shown to be true. I prove these in appendix C for the interested reader. The appendix use the values in table 2.1, which details the parameterization mentioned above and other parameters found in the model.

Table 2.1: Parameterization Used in Algorithm

Constant	Use	Low/High*
d	Constant used in state change in investment	.33, .6
g	Constant in state change from y	60
α	Scale coefficient for demand	2.49
β	Multiplicative coefficient for demand	-4.56
μ	Cost in dollars of dollars worth of investment	1
N	Maximum active firms	3
w^{MAX}	Highest efficiency level	12
$[X_{EL}, X_{EH}]$	Entry cost interval	$[.05, .1]$
β	Discount factor	.925
ϕ	Scrap value of exit	0.05
γ_1	scale marginal cost factor	1
γ_2	log-scale marginal cost factor	.449
f	Common CP fixed cost	1
Υ	Platform investment values	$\{.05, .2\}$
s^0	Industry initial state	$\{6, 0, 0, \ldots\}$
$\delta(y)$	More attractive outside opportunity	$\{\frac{1}{4}, \frac{1}{13}\}$
$c(p)$	Marginal platform cost	.033
*: Platform investment levels		

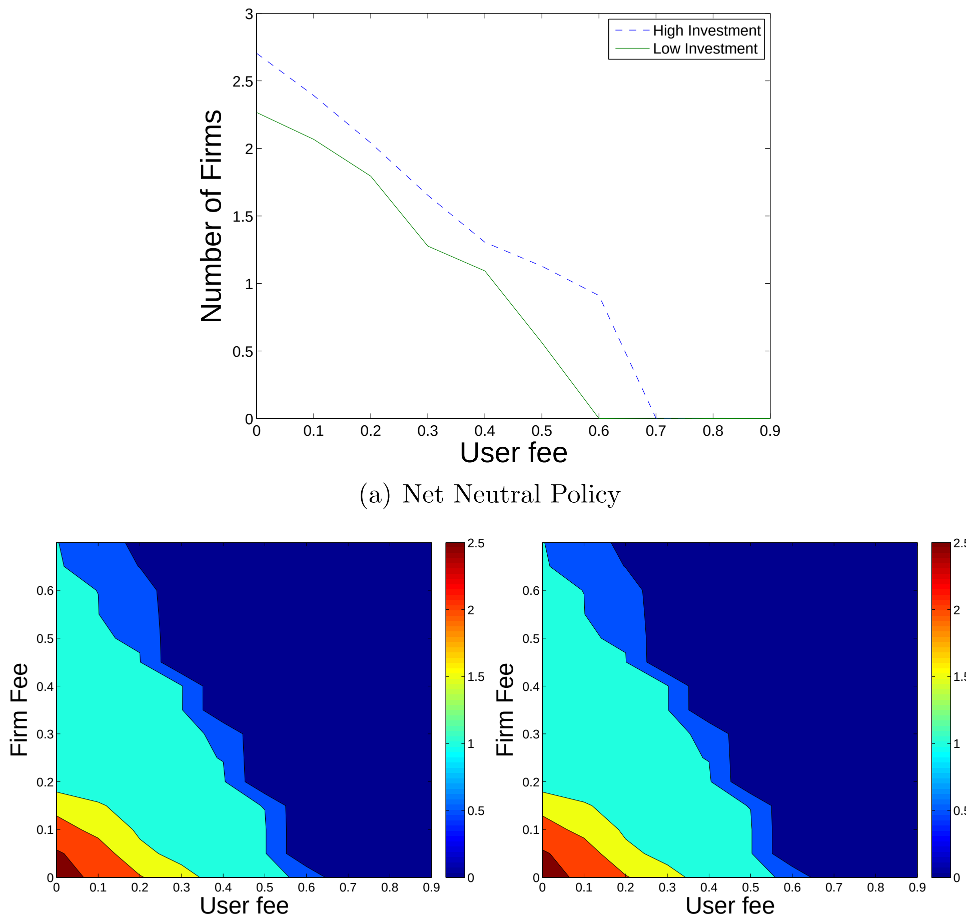
2.4 Results

As can be readily seen in the platform portion of the model, static platform profits are strictly decreasing in investment. We then observe whether a dynamic platform will choose a high level investment under a neutral network regime, or if warranted regulation could add benefit to the market. To observe this I show simulation results for market outcomes the average number of firms for each simulated $\{a_f, a_b\}$, the stability of the initial investment choice, and the welfare levels under network neutral regimes.

2.4.1 Market outcomes

This section details average count of content producers in the market, firm survival average, and average level of investments of these firms. Figure 2.1 details the average number of firms in the market over the course of the simulation. The contour plot shows the values at the range of user and content producer fees a platform would charge. The firm fee is limited to .7 (or 70 percent of revenue from a content-producer firm); the user fee is limited to .9 as the market unravels before this value. Table 2.2 shows these values under a network neutral policy. Both a high investment policy and a low investment policy increasing the user fee decreases demand, resulting in lower firm counts. However, under a lower platform investment policy, mean firm counts are decreased.

Figure 2.2 reports average lifespan results for content producers in the the simulation. As expected, when platform fees a low, firms tend to live

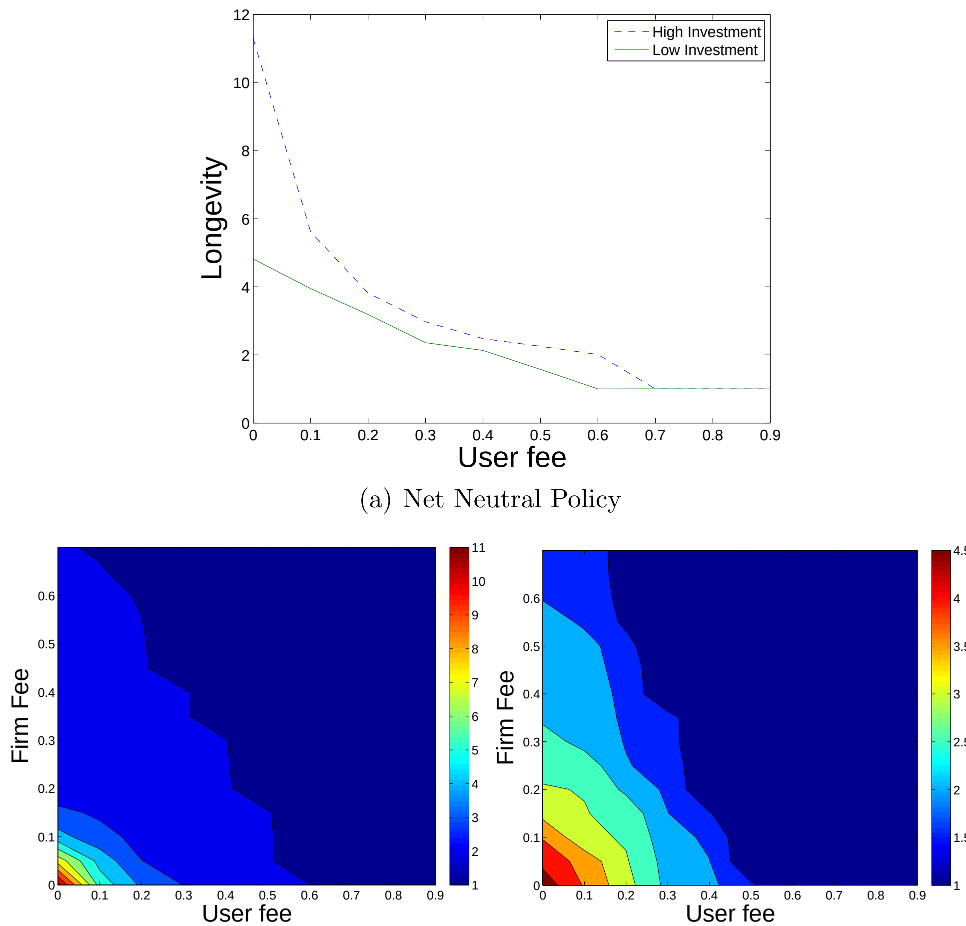


(a) Net Neutral Policy

(b) No Policy with high platform investment

(c) No Policy with low platform investment

Figure 2.1: Average Number of Firms



(a) Net Neutral Policy

(b) No Policy with high platform investment

(c) No Policy with low platform investment

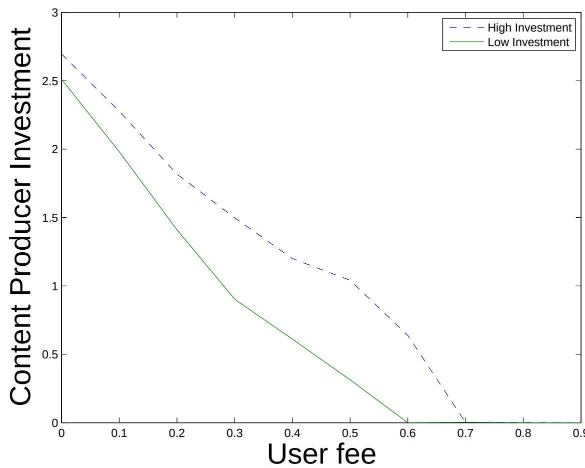
Figure 2.2: Average lifespan

Table 2.2: Average number of firms under network neutrality

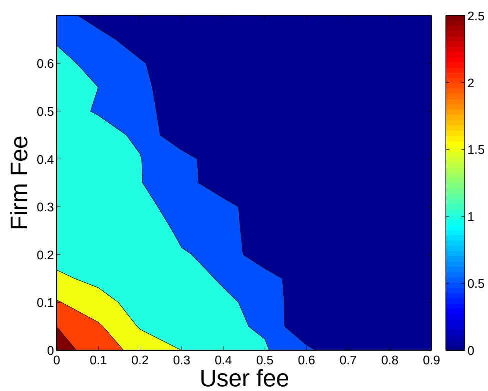
User Fee	High platform investment	Low platform investment
0	2.7	2.3
.1	2.4	2.1
.2	2.0	1.8
.3	1.7	1.3
.4	1.3	1.1
.5	1.1	0.6
.6	0.9	0.0
.7	0.0	0.0
.8	0.0	0.0
.9	0.0	0.0

longer. Most encouraging is that under low fees and a network-neutral policy content producers tend to last much longer with high investment by the platform. Once the user is charged an additional 60% (70%) by the platform for content produced under a platform low (high) investment choice firms tend to last only a period. Under no such restriction in policy, content producers tend to last for much longer periods of time under a high investment policy. This is due to idiosyncratic outcomes being more favorable to content producing firms with high platform investment.

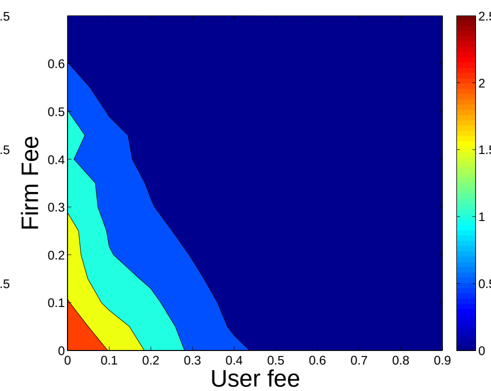
Figure 2.3 reports investment choices by content producers for the simulation. Recall that investment results a higher idiosyncratic probability of lower costs (higher firm efficiency) in following periods. A low platform investment regime indicates that content-producing firms tend to not invest. This you might expect from the model, this is correlated with expected lifespan.



(a) Net Neutral Policy



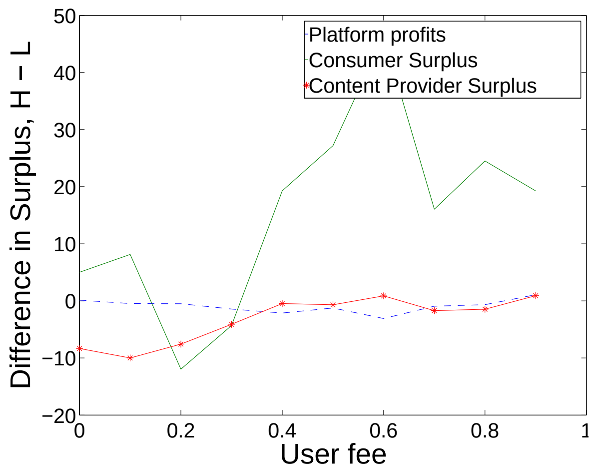
(b) No Policy with high platform investment



(c) No Policy with low platform investment

Figure 2.3: Average CP investment

Figure 2.4: Profit Differences with Neutrality



2.4.2 Welfare results

This section reports simulation results for content producers, consumers, platform providers, and total welfare. Contour maps with the full domain can be found in Appendix D.

Figure 2.4 details the total differences in the simulation. In general, both sides of the market receive higher welfare under a high investment regime with a neutrality regime. Platforms under this parameterization weakly receive more welfare under a low investment regime. Additional comparison for no neutrality policy can be found in figure D.1, which indicates slight differences for welfare across all firm fees, notably around a user fee of 0.3.

Figure 2.5 details welfare outcomes under the different platform regimes with network neutrality. In a network neutral regime a platform chooses a low-investment strategy for higher fees, and higher investment for lower userfees.

Figure 2.5: Platform Profit Comparison

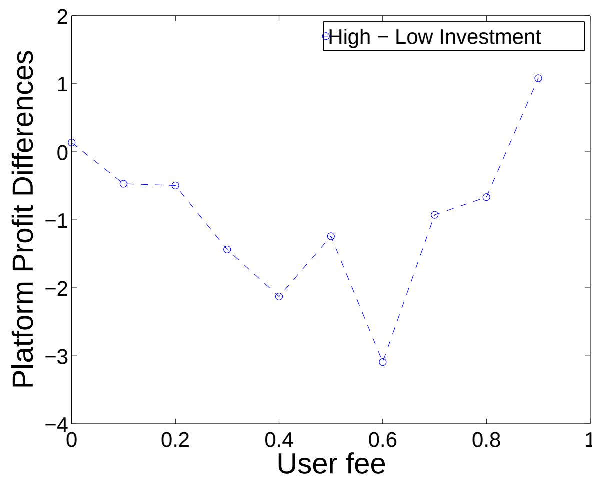
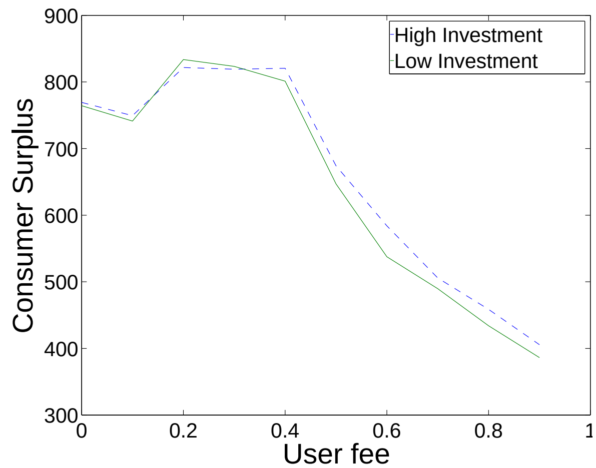


Figure D.2 also shows a contour map of platform profits under a high or low investment regime.

Consumer welfare in a network neutral regime can be seen in figure 2.6. With network neutrality consumer welfare results are mixed. For user fees less than 0.2 the difference is not statistically significant, implying true ambiguity on the issue. This result is further reflected in figure D.3, where the contours closely match (though there is significant differences as firm fees are increased).

Producer profits in a neutral regime can be seen in figure D.4. Notable here is that by allowing a *nonneutral* network regime results in significant higher profits for content producers. The reason for this is that users are not being directly charged; because of the nonneutrality of platform pricing schemes in a two-sided market under this parameterization firms end up with better outcomes under a nonneutral network.

Figure 2.6: Consumer Surplus Comparison



2.5 Conclusions and Limitations

This paper develops a framework to investigate dynamic decisions of players in two-sided markets. The particular focus is on the impact of network neutral policy on platform investment decisions in the provision of internet services and content production and consumption. Under a reasonable parameterization built from the current literature on ISP demand and engineering estimates, I have shown that ISPs will be unlikely to invest regardless of network neutral policy. However, welfare results under some platform choices indicate that more investment by the platform can be welfare enhancing. This strengthens the results of Choi and Kim [2010], and allows for some ambiguity in dynamic platform decisions to be cleared. Further, this shows policy makers that some form of regulation may be required for platforms to increase investment expenditures.

The framework can be extended to address some limitations that should be considered in using this framework for empirical studies.

- The parameterization used in the simulation is pulled from numerous industry reports and news sources close to industry insiders. A better parameterization would require data from ISPs and CPs on demand and costs.

- One observes that platforms occasionally enter the industries they hosts, such as in the case of cable, smartphone apps, or software production by operating system providers. This is not modeled for in this paper. However, this may be of particular importance in the ISP/CP video delivery industry, as many of the major broadband ISPs also operate in cable television markets under geographic monopolies for cable services. One can readily see a time-consistency issue with holding the platform firm fee constant through time under this assumption, and antitrust issues the ISP may impose on the market through tying and bundling.

- I assume away multihoming and platform competition. Relaxing this assumption can be modeled by making an extension in the direction of the work of Lee [2013] and Rochet and Tirole [2006].

These limitations make clear that the question of dynamic platform incentives requires further studies.

Chapter 3

Determinants of Retail Electricity Firm Failure

3.1 Introduction

Electric retail firms in deregulated markets provide electricity service to end consumers who vary in response to real-time market prices and procure from wholesale generators that respond in real time to aggregate electricity demand. In this capacity, retail firms behave similar to brokers: firms procure energy through bilateral contracts from generators or on the wholesale market. By minimizing their input costs, retail firms are able to undercut competitors in price competition on the retail market. Since 2002, the deregulated Texas market has seen more than 175 competitive retailer entrants, of which over 34% failed.

The prevailing wisdom in restructured markets is that entrants that last are generally retail firms with more sophistication through experience in other restructured markets or via hedging strategies. To asses the validity of these hypotheses, I examine plausible factors on exit rates of retail electricity firms from the beginning of deregulation until the zonal period's end in 2010. These impact factors include wholesale market pricing and volatility, transmission congestion, unemployment rate at time of firm entry, transmission regime upon entry, and previous firm experience in restructured electricity markets.

Understanding the effect of these variables in the electric retail market are essential to the long-term success of deregulated electric market systems. The ultimate reasoning for deregulation is that it increases efficiencies through competition. This paper addresses impediments to these efficiency gains; if risk factors keep retail firms from successfully implementing these efficiencies, deregulation is not achieving its policy goals.

I find that firm experience in other restructured markets does give an advantage to firm duration, especially with respect to initial economic conditions. However, I find no firm experience advantage to systemic risk factors such as price, congestion, and respective volatilities, which weighs as evidence against a hedging hypothesis explaining firm exit.

The rest of this chapter is organized as follows: section 3.2 details the institutions of the retail market, section 3.4 reports summary statistics for the data used in this study, section 3.3 catalogs the various hypotheses, models, and assumptions used in analysis, section 3.5 conveys the results of this analysis, and section 3.6 records the conclusions and areas for expansion and future work.

3.2 Institutions

The Texas electricity market consists of a number of different actors, including the public utility commission (PUC), the independent transmission operator (ERCOT), electricity producers, transmission and distribution systems, retail firms, and end-consumers. Additional to these primary actors are power marketers that provide liquidity, aggregators that represent aggregate end-consumer purchasing interests, and reliability service providers ensure continual operation of the transmission grid.

Retail firms act as brokers between generators and end consumers by operating in two markets. The first is the wholesale market, where a retail firm may procure energy through long-term bilateral contracts, day-ahead purchasing on the ERCOT platform, or the fifteen-minute ahead residual ("real-time") ERCOT market. The second is the retail market, where retail firms compete for customers in deregulated areas of the state.[1] Retail firms gain customers through a state-run online web portal where residential consumers can sign up for energy services, through aggregators, or through standard marketing practices.

Costs that retail firms face include traditional overhead and operation, wholesale purchase, and transmission delivery (which varies by customer types and transmission system that retail customers are connected to). These costs are risk to a retail firm. Wholesale purchasing exhibits the largest volatility:

[1]This area constitutes roughly 75% of the geographical area and 85% of demand within the ERCOT area.

prices in the wholesale residual market can vary to an upper price cap to below zero (to encourage shutdown of generator).[2] These prices generally affect retail firms that do not hedge, as firms that have purchased long-term bilateral contracts are not required to purchase energy in the residual market to cover their demand service requirements.

Conditions in the wholesale market can vary greatly due to shocks on the system. One of these conditions are represented by *congestion*, which is where a transmission system passes over a capacity threshold on at least one line or station within the system. Because of Kirchoff's power laws, one cannot easily segregate these lines, meaning that once one part of the system is congested the entire system interconnection is. This is important because part of the function of the residual market, in addition to ensuring supply always equates demand at every instant, is to adjust the price retail firms pay to effectually deal with congestion. Hence congestion represent systemic risk to all retail firms.

Another source of risk is wholesale price. Wholesale prices represent longer term systemic risk to retail firms. Retail firms typically write term-length contracts with end-consumers. Once these contract tenures expire end-consumers are put on a variable monthly rate. Newer retail firms, which may have a larger percentages of consumers on fixed unit-price contracts, would

[2] In discussions with aggregators, it was indicated that one sign of financial health aggregators look for in a retail firm is their percentage of purchasing on the day-ahead and residual markets; to aggregators less day ahead or retail purchasing indicates stability in a retailer.

experience more risk than other retail firms (this is a consequence of low consumer switching rates. See Hortacsu et al. [2012]). This additional risk could in turn represent impetus to exit. From a practical standpoint, this concern is somewhat moot. Hortacsu et al. [2012] and Defeuilley [2009] both point out that switching rates of end-consumers between retail firms is on average very low. This low rate indicates that consumers are generally being moved to a variable rate anyway after remaining with the same company. Table 3.1 details Texas' and other's switching rates As Defeuilley [2009] notes, these low switching rates (especially in European countries) are usually due to an incumbent's regulated rates being lower than market rates offered to end-consumers. Texas did not experience this phenomenon to the extent of other countries, especially after 2006 when regulation of incumbent retail rates expired.

Finally, transmission and distribution delivery fees represent another cost to retail firms. These fees are set by the Public Utility Commission to recoup costs a transmission company incurs in it's delivery. The volatility of these fees is low: the rates are announced long before implementation, and do not change often. Retail companies pay both the wholesale price and the transmission price to procure and deliver energy.

3.3 Model

Section 3.2 details the econometric model to assess the impact of various factos on risk of exit from the retail market. To assess this risk, I analyze the market for impacts of different risk factors. I assume that each of these factors

Table 3.1: Switching Rates as of 2006

Deregulated Area	Year Deregulated	Switching Rate Rate	Annual Switching Rate
South Australia	2003	34%	11.33%
Victoria (Aus.)	2002	45%	11.25%
Texas	2002	36%	9%
Netherlands	2004	15%	7.5%
Great Britain	1999	47%	6.71%
Sweden	1999	32%	4.57%
Belgium	2003	12%**	4%
Norway	1997	28%	3.11%
France	2004*	6%	3%
Spain	2003	7%	2.33%
Ohio	2001	8%	1.6%
Finland	1998	11%	1.38%
New York	1999	11%	1%
Germany	1998	7%	.88%
Massachusetts	1998	7%	.88%
Denmark	2003	2%	.67%
Pennsylvania	1997	3%	.33%
Connecticut	2000	2%	.33%
Maine	2000	1%	.17%

Information from Defeuilley [2009]
* Nonresidential, opened to full deregulation in 2007
** Flanders, exclusively

are exogenous.

I estimate a selection of covariate specifications using the Cox proportional hazard model [Cox, 1972] and Accelerated Failure Time models [Wei, 1992].

I use these models to estimate covariate impact on the firm exit hazard function

$$\lambda(t; \mathbf{X}) = \lim_{h \downarrow 0} \frac{P(t \leq T < t + h | T \geq t, \mathbf{X})}{h} \tag{3.1}$$

where T is random variable for the month of exit and X is a covariate set. Provided the cumulative distribution function is differentiable, equation 3.1 can be rewritten as

$$\lambda(t; \mathbf{X}) = \frac{f(t|\mathbf{X})}{1 - F(t|\mathbf{X})} \tag{3.2}$$

with $f(\cdot|\mathbf{X})$ as the probability density function and $F(\cdot|\mathbf{X})$ as the cumulative density function.

The Cox proportional hazard model (CPH) formalized is

$$\lambda(t; \mathbf{X}) = \lambda_0(t)\delta(\mathbf{X}) \tag{3.3}$$

where $\lambda_0(t)$ is the baseline hazard function, and $\delta(\mathbf{X})$ is a nonnegative function of $\mathbf{X}$. For all specifications I use a linear specification

$$\lambda(t; \mathbf{X}) = \lambda_0(t) \exp X\beta \tag{3.4}$$

where the differing specifications look at inclusion of different covariates. I test the proportional hazards using standard methods.

The accelerated failure time model (AFT) formalized is

$$\lambda(t|\theta, \mathbf{X}) = \theta(\mathbf{X})\lambda_0(\theta(\mathbf{X})t) \tag{3.5}$$

where

$$\theta(\mathbf{X}) = \exp(-X\beta) \tag{3.6}$$

$$f(t|\theta(\mathbf{X})) = \theta f_0(\theta(\mathbf{X})t) \tag{3.7}$$

$$\log(T) = \beta'\mathbf{X} + \epsilon \tag{3.8}$$

and ϵ is independently distributed of the acceleration factor θ. The accelerated failure time model has the beneficial property that it is robust to omitted variable bias.

The advantage to using the AFT model is that we are able to observe if certain conditions a firm faces increases or decreases exit pressure.

Either of these models serve as structural equations under an assumption of perfect competition. As I have not specified the competition environment, I leave this model open to being a reduced-form analysis only.

3.4 Data

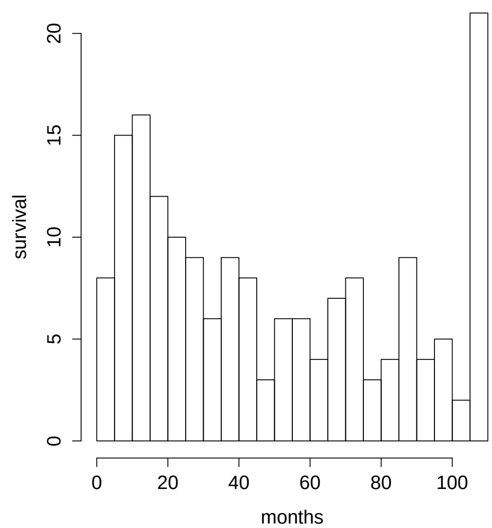
Data for this project comes from the same dataset as chapter 1. This is a combined dataset using information from ERCOT, PUCT, EIA, and NOAA.

The item of interest is number of months of retail firm engagement in the wholesale market. In table 3.2 *duration* is the length of spells for all

Table 3.2: Summary Statistics

Name	Average	Median	Standard Deviation	Max	Min	First Quartile	Third Quartile
Duration	48.7	42	35.08	106	1	16.5	82
Exitors	29.8	23.5	23.92	92	1	10	43.25
Whole Price	44.83	45.42	10.58	104	20.95	35.6	49.35
Whole Price σ	56.31	53.12	20.80	205.3	25.05	50.07	63.69
Congestion %	12.05%	11.11%	3.86	39.02%	5.38%	10.46%	12.41%
Congestion σ	28.97	28.19	3.61	47.8	21.26	27.1	30.31
Experienced Firm	.274		.447				
Unemployment Rate	6.16	5.7	1.64	9.9	4.4	5.1	6.05

Figure 3.1: Histogram of Firm Survival



firms, *exitors* reports the spell duration for exited firms, *Wholsale price* and *wholesale price* σ are the average wholesale price and volatility, respectively, *congestion % and congestion* σ are the percentage of times the residual market was in a congested state and the volatility of that state occuring within a month. *Experienced firm* refers to incumbents or firms that, before opening in the Texas market, operated within other deregulated markets, and the *unemployment rate* is the US unemployment rate for the month the firm entered the market. Figure 3.1 reports the histogram of firm survival. There are a total of 175 retail firms that engage in operation during the period, with 60 exits. These numbers do not include financial-only firms, as these types of firms were not included in ERCOT final settlement (financial-only firms do not have end-consumer clients). Nor do these numbers include cooperatives or municipal providers, as these geographic monopoly participants purchase on the wholesale market but do not compete for customers. These numbers include retail firms who had end-customers subscribed.

Firms listings come from ERCOT LSEGUFE data from 2002–2010. Firms are counted as active when first appearing in system data. Firms are considered as exited if before November 2010 (the last month of the dataset) they no longer have any energy credited to their company. I cannot separately identify mergers and acquisitions from bankruptcies in the data, and thereby assume any cessation of firm activity represents a firm exit.

Wholesale price and volatility data come from ERCOT's *Market Clearing Price for Energy* reports aggregated across zones; this data published at the same frequency as the LSEGUFE quantity data. Congestion is inferred from this same data source, as the zonal markets are in lockstep in uncongested conditions and operate independently when congestion is experienced on the network.

Experienced firm data comes from reviewing retailer history information and press releases. The unemployment rate comes from the St. Louis Federal Reserve FRED database, civilian unemployment rate covering the zonal period.

For the regression I also include information on distinct transmission rate regimes when the firm enters. These are derived as follows: Centerpoint, the largest transmission firm, had their rates changed at the end of period 1. AEP Texas Central Company, AEP Texas North Company, and Oncor had their rates changed at the end of period 2. Texas-New Mexico power had their rates changed during period 3, but the effect was small. TNMP is more than an order of magnitude smaller than the two largest transmission firms, and the rates were changed by a low 5 percent.

3.5 Results

3.5.1 Cox Proportional Hazard Model Results

Table 3.3 reports a selection of numerous specifications for the Cox proportional hazards model. Here P is monthly average wholesale market purchase price, $\sigma(P)$ is monthly wholesale market purchase price volatility, C is average monthly congestion percentage, $\sigma(C)$ is the volatility of said congestion, u is the civilian unemployment rate, E is an indicator whether the firm has previous experience in other restructured electricity markets, and periods 1 and 2 are indicators of the transmission regime the firm begins in (period 3 being the default).

The response to price, congestion, and respective volatility are indicative with how well firms handle these systemic issues. Positive coefficients indicate increased likelihood of failure, and negative values the reverse. So as table 3.3 indicates, the likelihood of failure *decreases* with increases in volatility to prices or congestion. This perhaps counterintuitive finding may be explained by high price and congestion spikes occurring less frequently than

Table 3.3: Proportional Hazard Specification Results

Hazard	1	2	3	4	5	6	7	8	9
P	.209***	.197***	.257***	.243***	.255***	.243***	.255***	.300***	.330***
	(.029)	(.029)	(.035)	(.035)	(.036)	(.035)	(.036)	(.032)	(.037)
$\sigma(P)$	-.096***	-.096***	-.100***	-.100***	-.110***	-.101***	-.106***	-.203***	-.201***
	(.015)	(.0146)	(.015)	(.015)	(.015)	(.016)	(.016)	(.023)	(.024)
C	1.79***	1.79***	2.02***	2.04***	2.17***	2.05***	2.17***	1.97***	2.23***
	(.268)	(.261)	(.285)	(.278)	(.288)	(.294)	(.303)	(.224)	(.264)
$\sigma(C)$	-1.23***	-1.22***	-1.35***	-1.36***	-1.46***	-1.36***	-1.46***	-1.29***	-1.47***
	(.259)	(.248)	(.261)	(.251)	(.257)	(.254)	(.260)	(.208)	(.224)
u			1.35***	1.30***	1.45***	1.30***	1.45***		.698***
			(.337)	(.320)	(.322)	(.321)	(.323)		(.256)
E		-.776**		-.824***	17.9**	-.996	17.8**		14.27*
		(.341)		(.343)	(7.12)	(1.67)	(7.45)		(8.29)
P*E						.004	.001		.003
						(.038)	(.004)		(.005)
u*E					-3.28***		-3.28***		-2.36*
					(1.26)		(1.26)		(1.39)
Period 1								-6.48***	-6.22***
								(.916)	(.949)
Period 2								-1.80*	-1.72
								(1.09)	(1.61)
R^2	0.49	0.506	0.522	0.538	0.55	0.538	0.55	0.633	0.656
LR	117.9	125.6	129	135.3	139.5	135.3	139.8	175.4	187
Wald	73.8	81.62	80.24	85.42	87.81	85.35	87.79	112.9	115.7
DF	4	5	5	6	7	7	8	6	10

N=175 Failures= 60

***: 99% Significance Level, **: 95%, *:90%

low spikes or longer lulls. Higher unemployment rates increasing the rate of exit makes intuitive sense, as a systemic poorer economy at the time of a business launch makes for more difficult initial start. Experienced firms have an overall advantage in this market, but as specifications (5), (7) and (9) indicate, this advantage is actually due to experienced firms being able to weather bad economic conditions more successfully than less experienced firms, as we would expect. However, no specification shows that experienced firms handle prices better than less-experienced firms.[3] With these specifications entering during the first transmission regime is correlated with decreased likelihood of exit. There are a number of possible explanations for this, including that the transmission rates during this period are somehow more preferential, or, more likely, firms engaged in the earlier periods faced less competition and more time to gain a foothold in the market.

The fact that experienced firms handle prices no better than inexperienced firms, that experienced firms handle poor initial economic conditions better than inexperienced firms, and that any firm that enters during an earlier time period has a shot at a longer duration are indicative that there may be institutional factors within the Texas market specifically that require experience for a firm to experience, but outside experience does not unequivocally guarantee a longer expected duration.

Table 3.4 reports p-values for proportional hazard testing. The null hy-

[3]This holds true as well for specifications (not reported here) that include interactions between E and congestion and various volatility.

pothesis is that the parameter (or model) has a multiplicative constant effect over time. As can be seen, prices, congestion, and respective volatility gen-

Table 3.4: Proportional Hazard Test p-Values

	1	2	3	4	5	6	7	8	9
P	.005	.005	.345	.317	.461	.318	.453	.04	.076
$\sigma(P)$	.001	.001	.045	.051	.132	.065	.141	.11	.187
C	0	0	.008	.013	.046	.018	.051	.003	.08
$\sigma(C)$	0	0	.003	.006	.02	.006	.021	.006	.048
u			.537	.671	.643	.673	.655		.744
E		.811		.983	.557	.961	.541		.163
P*E						.965	.861		.176
u*E					.545		.539		.069
Period 1								.271	.099
Period 2								.389	.108
Model	6.8*10^7	4.9*10^-5	.003	.015	.042	.029	.069	.075	.159

erally fail to exhibit proportional hazards. Experience and unemployment do exhibit proportional hazards. The interactions between prices, unemployment, and experience do suggest proportional hazards. All but the last specification indicate that the respective models can have the null hypothesis of proportional hazards rejected.

3.5.2 Accelerated Failure Time Model Results

This section reports AFT specification results for both exponential and Weibull distributions in table 3.5.

Table 3.5: Accelerated Time Failure Estimates

log(T)	1	2	3	4	5	6	7	8	9
Constant	1.24	1.08	1.73**	1.58*	1.64*	1.49***	1.54*	-.25	-.25
	(.781)	(.717)	(.993)	(.874)	(.834)	(.885)	(.85)	(.545)	(.557)
P	-.031***	-.028***	-.032***	-.029***	-.029***	-.029***	-.029***	-.036***	-.034***
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.003)	(.003)
$\sigma(P)$	.02***	.02***	.02***	.02***	.02***	.018***	.018***	.029***	.024***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.002)	(.003)
C	-0.18***	-.18***	-0.174***	-.174***	-.177***	-.167***	-.17***	-.2***	-.183***
	(.035)	(.032)	(.035)	(.032)	(.032)	(.032)	(.032)	(.024)	(.023)
$\sigma(C)$	.099**	.099***	.091**	.091*	.094**	.097**	.101**	0.123***	.125***
		(.036)	(.041)	(.036)	(.036)	(.037)	(.037)	(.026)	(.025)
u			-.054	-.056	-.075	-.064	-.083		-.015
			(.071)	(.06)	(.057)	(.059)	(.056)		(.022)
E		.158***		.160***	-1.88*	-.33	-2.65**		-2.15**
		(.06)		(.06)	(1.14)	(.371)	(1.24)		(1.01)
$P * E$						.011	.012		.014*
						(.008)	(.008)		(.007)
$u * E$					.359*		.399**		.281*
					(.202)		(.202)		(.165)
Period 1								.924***	.847***
								(.01)	(.095)
Period 2								.271**	.36*
								(.137)	(.186)
Scale	.195	.188	.195	.187	.185	.184	.182	.129	.12
LR	93.2	126.88	93.8	101.8	104	103.8	106.6	167.2	175.4
DF	4	5	5	6	7	7	8	6	10

N=175 Failures= 60

***: 99% significance level, **: 95%, *: 90%

As before, P is monthly average wholesale market purchase price, $\sigma(P)$ is monthly wholesale market purchase price volatility, C is average monthly congestion percentage, $\sigma(C)$ is the volatility of said congestion, u is the civilian unemployment rate, E is an indicator whether the firm has previous experience in other restructured electricity markets, and periods 1 and 2 are indicators of the transmission regime the firm begins in (period 3 being the default). The constant here can be seen as the log time of duration for an unexperienced firm in period 3. The regressand here is $\log(T)$, the log-length of duration to exit; as this is an inverse to the hazard value parameters here with a reverse sign to that of the Cox proportional hazard table have a similar interpretation on increase or decrease of duration.

The findings in this section mostly support those of table 3.3, with the exception that the unemployment rate parameter fit is decreased, and some weak evidence in specification (9) that experienced firms have some better mechanisms at dealing with increased prices.[4] However, the evidence has marginal statistical significance at the 90% level.

3.6 Conclusions

This chapter has explored different factors affecting the likelihood of failure for retail electric firms in the Texas electricity market for the time period 2002–2010. There is evidence that experienced firms deal with initial

[4]As with the Cox proportional hazard specifications, interactions with volatility were inconclusive.

economic conditions better, but little evidence that these firms are able to handle price or volatility superior to that of inexperienced firms. This weights as evidence against the notion that more experienced firms has fundamentally stronger hedging strategies. Systemic risk affects firms as we'd expect. We can can conclude that experienced firms do have an advantage, but that this advantage is not a function of dealing with wholesale price pressure in systemically superior ways. This may imply that the Texas market has factors that previous experience may not prepare a retail firm to accommodate.

In order to establish sound policy recommendations, more research is needed to incorporate retail firm exit decision as part of a larger system of entry, investment, and industry dynamics. Additionally, the question whether apparent idiosyncratic restructured market factors drive exit rates, or if these factors are common across markets.

Appendices

Appendix A

Ramsey-Boiteux Pricing

Ramsey pricing (also known as Ramsey-Boiteux pricing) is a regulation framework that achieves the second-best welfare outcome. This is achieved by the regulator maximizing social welfare in a market consisting of a multi-product regulated firm.

Formally,

$$\max_{P_i} \sum_i SW_i(P_i) \quad \text{subject to} \quad \sum_i P_i Q_i(P_i) - C(\sum_i Q_i(P_i)) \geq F \qquad \text{(A.1)}$$

where C and F represent the firms variable and fixed costs of production respectively.

The set of prices $\{P_i\}$ which maximizes the sum of welfare can be characterized by the Lerner index

$$\frac{P_i - C_i'}{P_i} = \frac{\lambda}{1+\lambda} \frac{Q_i(P_i)}{P_i} \cdot \frac{\partial P_i}{\partial Q_i} \qquad \text{(A.2)}$$

where $C_i' = \frac{\partial C}{\partial Q_i} \frac{\partial Q_i}{\partial P_i}$ is the marginal cost in market i and λ can be interpreted as the social cost of relaxing the break-even constraint. This result a scaling of the inverse elasticity (or monopoly pricing outcome) by the relative impact on social cost (the $\frac{\lambda}{1+\lambda}$ term). For a comprehensive review, see Laffont and Tirole [1993].

Appendix B

Other specification results for chapter 1

B.1 Demand Specifications

This subsection reports the results of pooled OLS estimation and fixed effects across geographic zones, weatherzones, and firms. These results are found in B.1, which contains estimate results for weekly estimates.

B.1.1 Alternative Supply Specifications

This section includes an alternative supply specification considered: monthly average outcome estimates. These results are found in B.2.

B.1.2 Transmission Cost Specifications

An alternative cost specification of interest includes looking at average transmission cost per line-mile. Table B.3 records these estimates. I use a quadratic specification here, and note that the square term here is the sum of square observations over a quarter, rather than the square of the quarterly sum. One can see that the cost per line mile is roughly equivalent between all firms. However, this gives an interpretation that average costs (and more importantly, marginal costs) are increasing as a function of firm size. However, this does not correspond to what is understood about transmission firms, in

Table B.1: Monthly Demand Estimates in MWH

Type	BUS		BUSIDR		BUSNO		RES	
Model	1	2	1	2	1	2	1	2
$P+T$	-.3357613*	-.2386958	-.2535126	-.5343356†	-.0078412*	-.0050934	-.159881*	-.121531
CDD	.0015983*	.0009587	.0116759†	.0130115†	.0000412*	.0000278	.0008013	.0004829
HDD	.0048794*	.0044349*	.007369†	.0097037†	.0001279*	.0001184*	.0026114*	.0023867*
Constant	71.14437**	17.3745	115.2517†	250.666†	1.779212**	.3648948	34.41361**	9.250813
1^{st} FStat								

Supply shifters: windspeed, natural gas *
†: 99% significance level, **: 95%, *: 90%
1: Pooled IV regression
2: Zone, Weather zone, Firm fixed effects IV regression

Table B.2: GWh Monthly Zone Estimates, 2002 – 2003, 2007 – 2010

Zone	P_0	Gas	Windspeed	Constant
Houston	37.391†	-214.651†	-158.97†	2,946.24†
North	11.08†	-62.51†	-40.04†	797.69†
South	3.3**	-15.89†	-13.11†	456.17†
West	2.11†	-10.27†	-3.133	120.85†

P_0 instrumented by CDD and HDD
†: 99% Confidence Lever, **: 95%, *: 90%

that average costs are decreasing.

Table B.3: Alternative Transmission Costs Estimates

Variable	Cost-lines	Cost-lines firm-specific
CP		
q	-.0009798**	-.0018136
q^2	2.70e-06†	4.58e-6**
TCC		
q	-.0009798**	.0013078**
q^2	2.70e-06†	6.78e-7
TNC		
q	-.0009798**	.0016215
q^2	2.70e-06†	.0000198
TNMP		
q	-.0009798**	.0090386
q^2	2.70e-06†	.000438
TXU		
q	-.0009798**	.0006947†
q^2	2.70e-06†	-424e-7†
N	103	103
R^2	.67	.67

1: Cost
2: Firm-Specific Cost
Log
†: 99% significance level, **: 95%, *: 90%

Appendix C

Conditions proof for chapter 2

The Ericson-Pakes algorithm requires the following assumptions to hold in order to generate an MPE. I prove these hold for each subgame of platform choice $y \in \Upsilon$, and suppress the y notation for clarity.

1. $\omega \in \Omega \subset \mathbb{Z}$, $s \in S \subset \mathbb{Z}_{+}^{\infty}$, with $\succeq$ a complete pre-order on S.

2. $\beta \in (0, 1)$ and $\phi \in \mathbb{R}$

3. For every ω the marginal cost of investment $c(\omega) \in [\underline{c}, \infty)$, $\underline{c} > 0$

4. For every $s \in S$, reduced form profits $A(\omega, s, a_f, a)$ have the following properties:

   (a) $\lim_{\omega \to \infty} A(\omega, s) = \overline{A} < \infty$

   (b) $\lim_{\omega \to -\infty} A(\omega, s) \leq (1 - \beta)\phi$

   (c) $A(\cdot, \cdot)$ is nondecreasing in ω for all s

   (d) For all ω and s in $\hat{S}_n(\omega)$, $A(\omega, s) \leq (1 - \beta)\phi + o(\frac{1}{n})$, where $\hat{S}_n(\omega) \equiv \{s \in S \mid \sum_{\omega' \geq \omega} s_{\omega'} \geq n\}$

5. For every $\omega \in \Omega$ and for every $x \geq 0$, $p(\dot{|}\omega, x)$ is formed from the convolution of two distributions with finite support: $\pi(\cdot|\omega, x)$ with $\text{supp}(\pi) =$

$\{\omega'|\omega' = \omega + \tau, \tau = 0, 1, ldots, k_1\}$, $p_0 = \{p_\eta\}_{-k_2}^{0}$ with $\text{supp}(p_0) \subset \{\omega'|\omega' = \omega + \eta, \eta = -k_2, -k_2 + 1, \ldots, 0\}$. $\pi(\cdot|\omega, x)$ is stochastically increasing, continuous in x, $\frac{\partial \pi}{\partial x}(\omega|\omega, x) < 0$, , $\frac{\partial \pi}{\partial x}(\omega'/\omega, x) > 0$ and concave at each $\omega' \in \{\omega + 1, \ldots, \omega + n\}$ and $\pi(\omega'|\omega, 0) = 1(\omega' = \omega)$.

6. $m(s, y)$ firms enter each period, $m : S \times \Upsilon \to \mathbb{Z}_+$. Each entrant pays $x_e^m > \beta\phi$, nondecreasing in the number of entrants m. The entry process is completed at the beginning of the succeeding period, when each entrant becomes an incumbent at some state $\omega^0 \in \Omega_e \subset \Omega$ with probability $P(\omega^0) = \sum_{\eta=-k_s}^{0} p_\eta \pi^e(\omega^0 - \eta)$. Ω_e is a compact connected set.

7. There exists a regular Markov transition kernel $Q : \mathbb{Z}_+^\infty \times \mathbb{Z}_+^\infty \to [0, 1]$, or, alternatively,

$$\text{For every } B \subset S,\ \forall s \in S,\ \sum_{s' \in B} Q(s'|s) = \Pr(s_{t+1} \in B | s_t = s), \tag{C.1}$$

with range $S(s) = \{s'|Q(s'|s) > 0\} \neq \emptyset$, such that the functions $q_\omega(\hat{s}'|s) \equiv \sum_\eta q_\omega(\hat{s}'|s\eta)p_0(\eta)$ are the consistent marginal transition probabilities derived from it for $\hat{s} = s - e_\omega$. The stochastic kernels Q and q_ω have the Feller property, i.e. each maps the space of continuous functions $C(S)$ to itself

8. (a) There exists a constant $M < \infty$ such that, for all $s \in S, m(s) \leq M$.

   (b) The set of potential feasible industry structures $S \subset \mathbb{Z}_+^\infty$ is compact

Lemma C.0.1. $\sigma \equiv \frac{1-a_f}{1+a_b} \in [0,1]$.

Proof. Recall $a_f \in [0,1]$ and $a_b \in \mathbb{R}_+$. If $a_b = a_f = 0$, then $\sigma = 1$. α is clearly decreasing in a_f. At its highest, $a_f = 1 \Rightarrow \sigma = 0$ for all a_b. $a_b \geq 0$, and for all a_b, $\sigma > 0$. $a_b = 0 \Rightarrow \sigma = 1 - a_f$, and $\lim_{a_b \to \infty} \sigma = 0$. □

Lemma C.0.2. *The static profits as efficiency decreases is $-f$:* $\lim_{\omega \to -\infty} \pi_i = -f$. *In other words, $\exists \omega$ such that $\sigma P^* - \gamma_1 e^{-\gamma_2 \omega} < 0$ for every $(a_b, a_f) \in \mathbb{R}_+ \times [0,1)$ (given that $\gamma_2 > 0$).*

Proof. Clearly $c_i = \gamma_1 \mathrm{e}^{-\gamma_2 \omega_i}$ and the previously defined P^* are continuous over $\mathbb{Z}$.

In equilibrium,

$$\sigma P^* = \frac{\sum_j c_j - N\sigma\beta}{N} \leq \bar{c} - \sigma\beta \tag{C.2}$$

where $\bar{c}$ is the lowest cost. As ω_i decreases, $\gamma_1 \exp(-\gamma_2 \omega_i)$ increases. Then

$$\lim_{\omega \to -\infty} \bar{c} - \sigma\beta - \gamma_1 \exp(-\gamma_2 \omega) < 0 \tag{C.3}$$

by inspection. □

Theorem C.0.3. *The parameterization and construction of the simulated model meet the criteria for using the Ericson-Pakes algorithm to determine an MPE in each subgame denumerated by $y \in \Upsilon$.*

Proof. The proof addresses each portion line by line

1. I define $\Omega = \{0, 1, \ldots, 12\}$, and exit occurs by construction for efficiency draws $\omega < 0$. s is accordingly in $\mathbb{Z}_{+}^{\infty}$. Profits are weakly decreasing as other firms' efficiencies increase, thus, the pre-order property is satisfied.

2. $\beta = .925$ and $\phi = 0$ are used in the simulation.

3. Since $\max\{\Omega\} = 12$, $\gamma_1 \exp -5,388$ is the lowest cost. Set $\underline{c} = \gamma \exp -13.021 > 0$ and the condition is satisfied.

4. Define $A(\omega|s) \equiv \pi(q_i^*; \omega, s, a_f, a_b, y)$, the equilibrium profit choice. Fix N^* (only one firm at a time considered in exit decisions).

   (a) The first part of this proof requires me to show $\lim_{\omega} A(\omega|s) = \overline{A} < \infty$. I show that π_i is bounded in the limit piecewise.

   From earlier, we see that the equilibrium price P is

$$P^* = \alpha + \beta \ln(\sum_i q_i) = \frac{\sum_i \gamma_1 \exp(-\gamma_2 \omega_i) - \sigma\beta}{N\sigma} \tag{C.4}$$

   Then, in the limit,

$$\lim_{\omega_i \longrightarrow \infty} P = \lim_{\omega_i \longrightarrow \infty} \frac{\sum_j \gamma_1 \exp(-\gamma_2 \omega_j) - \sigma\beta}{N\sigma} \tag{C.5}$$

$$< \lim_{\omega_i \longrightarrow \infty} \frac{N\gamma_1 \exp(-\gamma_2 \omega_i) - \sigma\beta}{N\sigma}$$

$$= -\frac{\beta}{N} \tag{C.6}$$

   q_i is bounded by the same limit as P^*.

Finally,

$$c_i = \gamma_1 \exp(-\gamma_2 \omega_i) \longrightarrow 0 \tag{C.7}$$

(b) As seen in part (4a), $\lim_{\omega_i \to -\infty} q_i < \lim_{\omega_i \to \infty} \sum_j q_j = 0$. Then $\lim_{\omega_i \to -\infty} \pi_i = 0 \leq (1-\beta)\phi = 0$

(c) This portion can be shown to hold directly.

$$\frac{\partial \pi_i}{\partial \omega_i} = \frac{-\gamma_2 c_i}{N\sigma} - \gamma_2 c_i q_i \geq 0 \tag{C.8}$$

where $0 \geq \sigma \leq 1$ and $N > 0$

(d) The last item follows by construction, and is checked by the algorithm in the fixed static profit matrix.

5. The convolution are discussed in the laws of motion sections 2.2.2.3 and 2.2.2.4, and in the simulation introduction.

6. $x_e^m \in [.05, .1]$ for $m \leq 3$, and ∞ otherwise. $\beta\phi = 0$.

7. Follows from previous explanation. a_f and a_b have no direct impact on the probability transition kernels. See Pakes, et al. (1993) for more details.

   (a) $m(s) \leq 3$ by construction for every s.

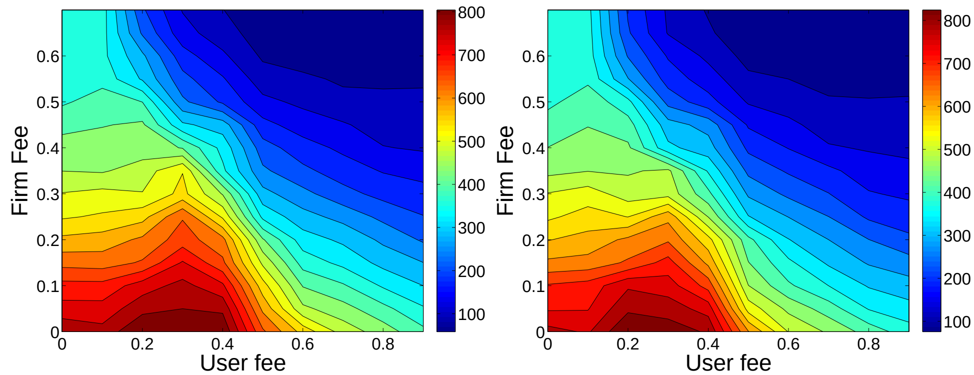
   (b) $\Omega = \{0, 1, \ldots, 12\}$. The set $S = \{0, 1, 2, 3\}^{29}$ is finite, so S and any nonempty subset is necessary compact.

□

Appendix D

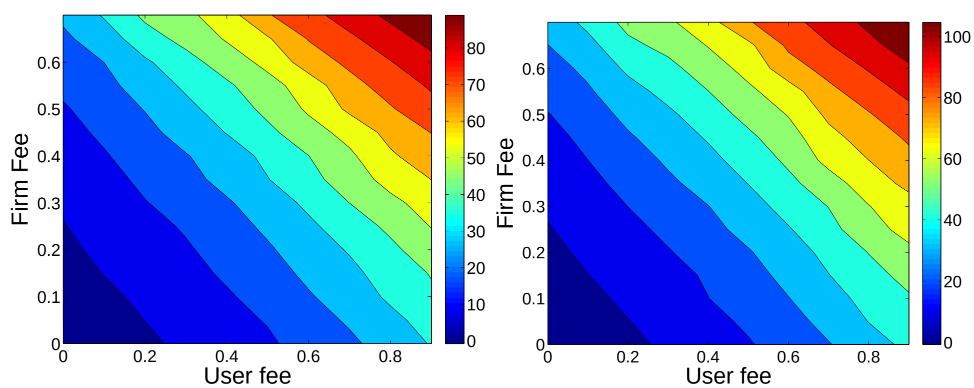
Net Neutrality Welfare Figures

This appendix include figures from section 2.4.1.



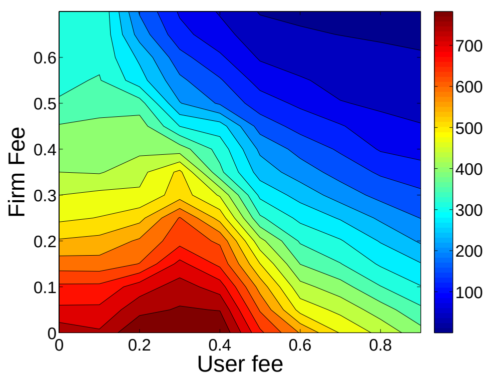
(a) High platform investment (b) Low platform investment

Figure D.1: Average Total Welfare Comparison

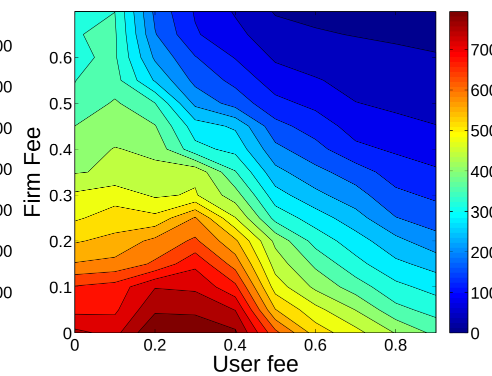


(a) High platform investment (b) Low platform investment

Figure D.2: Average Platform Profits Comparison

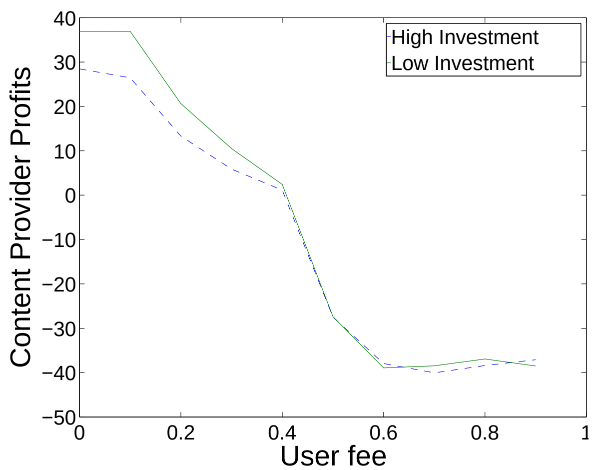


(a) No Policy with high platform investment

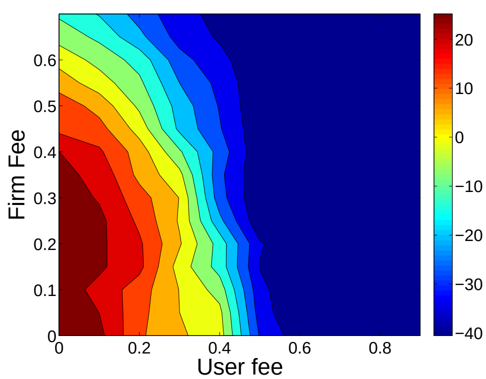


(b) No Policy with low platform investment

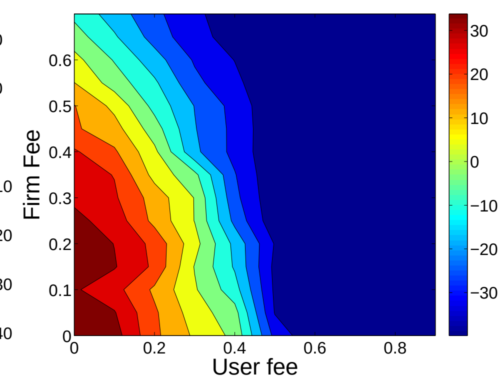
Figure D.3: Average Consumer Surplus Comparison



(a) Welfare with Network Neutrality



(b) No Policy with high platform investment



(c) No Policy with low platform investment

Figure D.4: Average Producer Profits Comparison

Appendix E

Code link

The interested reader may find a portion of the ISP/CP network neutrality analysis working code at
https://sites.google.com/site/thomasroderick/research.

Matlab and Gauss code for the original Pakes, et al. encoding of the Ericson-Pakes algorithm is warehoused at
http://www.economics.harvard.edu/faculty/pakes/program

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Vita

Thomas Edward Roderick was born in Houston, Texas, on 27 July 1983, the son of Homer Edward Roderick and Susan Gayle Roderick (*neé* Dempsey). He was raised in Joshua, Texas, and later lived in the Philippines for two years where he taught English, performed community service, learned 4 local dialects, and worked in proselyting and ecumenical roles as a missionary for the Church of Jesus Christ of Latter-day Saints. Upon returning, he re-enrolled in Brigham Young University in 2004 and received a Bachelor of Science degree in Mathematics and an additional degree in Economics from Brigham Young University in December 2007. He then worked in an engineering role with TAC Americas (now Schnieder Buildings), where he ensured contract compliance and performance assurance of building retrofitting in the Energy Solutions division. He left TAC in May of 2009 and worked for Woot, Inc., a subsidiary of Amazon, before entering graduate studies at the University of Texas at Austin Department of Economics in August of 2009. At the time of writing he is the happy father of two young children and the lucky husband of Ms. Katie Pauline Roderick.

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