Essays on Knowledge Sharing and an Opt-in Evaluation Process among Investment Professionals

by

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For my parents who taught me to follow my passion,
Kate who supports me in all that I do, and
Rowan who inspires me every day

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Abstract

This dissertation contributes to our understanding of recently popularized opt-in evaluation processes. These processes have been democratized such that ratings are provided no longer solely by experts, but commonly by any audience member who has experienced an offering (i.e., good, candidate, or service) and chooses to rate its quality. The goal of these democratic evaluation processes is to collect independent ratings from evaluators in order to triangulate on a representative and unbiased signal of quality. Across the three chapters of this dissertation, I study various aspects of an opt-in evaluation process to uncover the mechanisms that affect evaluative outcomes. To do so, I use data from an online knowledge-sharing platform and its opt-in evaluation process in the investment management industry where investment professionals share investment recommendations. In Chapter 1, to gain a better understanding of the platform under study, I focus on the conditions that bring these professionals together to engage in knowledge sharing, despite the associated risk of losing competitive advantage. In Chapters 2 and 3, I turn my focus to the evaluation process, in particular, examining who opts to evaluate and how factors unrelated to an offering's quality affect the evaluative outcomes. Chapter 2 examines how social influence, measured as exposure to the ratings from past evaluators, affects the likelihood that subsequent ratings occur and the types of ratings an offering receives. Chapter 3 examines how search costs and uncertainty facing an evaluator affects the likelihood of gender bias in the amount of attention and types of ratings an offering receives.

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Introduction

Across many contexts, actors struggle to identify the expected quality of offerings (i.e., candidates, goods, or services) they have not directly experienced. To remedy this issue, individuals and firms often rely on ratings of quality from others. Historically, experts or professional critics provided this information (Hsu 2006; Zhao and Zhou 2011). More recently, there has been a major shift in how quality ratings are collected and who provides these evaluations; namely the evaluation process has become democratized (Dellarocas 2003). Any audience member who has experienced an offering has a plethora of platforms on which they can opt to share their rating of quality (e.g., BeerAdvocate, Healthgrades, TheFunded, Yelp). Furthermore, many firms provide a similar opt-in evaluation process, allowing their users to rate the quality of the offering they provide (e.g., Airbnb, TaskRabbit, Uber, Upwork). The goal of these democratic evaluation processes is to collect independent ratings from evaluators in order to triangulate on a representative and unbiased signal of quality. Moreover, apart from being prevalent, the ratings these opt-in evaluation processes produce have a significant effect on individual and firm success (e.g., Chevalier and Mayzlin 2006; Clemons, Gao, and Hitt 2006; Luca 2016; Melnik and Alm 2002; Erbentraut 2015).

This shift is due in large part to the proliferation of the digital (and sharing) economy, given the inherent uncertainty and difficulty of establishing trust and knowing an offering's quality *ex ante* (Sundararajan 2016). For example, it would be challenging to convince an individual to stay in the home of a stranger or for a firm to hire a group of freelancers without supplying some signal of quality for that offering. The demand for, or at least expectation of being able to access, ratings of quality for an offering has led to different types of opt-in evaluation processes becoming a strategic tool utilized within organizations, industries, and markets. However, less is known about these types of opt-in evaluation processes, in particular the factors that affect evaluative outcomes.

In this dissertation, I develop a better understanding of various aspects of these democratized, opt-in evaluation processes using data from a knowledge-sharing platform in the investment management industry. The context for this dissertation is the Real Investors Club (RIC, a pseudonym), an online platform that facilitates knowledge sharing among buy-side (e.g., hedge fund, mutual fund) investment professionals. On RIC, investment professionals simultaneously act as producers, openly sharing investment recommendations, and as audience members/evaluators, reading and rating (anonymously) the recommendations of others. Each of the three chapters of this dissertation presents an independent research paper that examines the mechanisms that affect the evaluation process on RIC. Before studying the evaluation process, it is important to first understand the knowledge sharing that occurs in this setting, namely the investment recommendations and related analysis, since this is the offering being evaluated in this context. I begin, in Chapter 1, by identifying the conditions under which these professionals share their in-depth stock analysis, since it is a main source of their competitive advantage. I then, in Chapters 2 and 3, turn my attention to the evaluation process itself, uncovering the factors that may interfere with the underlying goal of these processes: to collect unbiased ratings of quality.

In Chapter 1, "Here's an Opportunity: Knowledge Sharing among Competitors as a Response to Uncertainty," I examine the conditions that help sustain knowledge sharing among competitors. In order to build a comprehensive understanding of any evaluation process, it is necessary to first consider why actors subject their offering (here, recommendation) to evaluation, particularly when doing so risks losing competitive advantage. This is especially important in organizational and market contexts where evaluations are not the primary goal, but rather a by-product of an exchange. I build my argument from the viewpoint of an entrepreneur who has discovered an opportunity in their market. Drawing on extant organization and strategy research showing that there are sometimes positive externalities from interactions with competitors, I posit that actors are motivated to share knowledge about an opportunity they have discovered, even when doing so risks loss of competitive advantage, as a strategic response to uncertainty. Specifically, in markets where buy-in from one's competitors can increase the probability that a given opportunity is successfully exploited, knowledge sharing can facilitate the coordination of these key resources. To do so, I leverage a unique feature in my context, where actors are able to share an opportunity with or without including the analysis that supports it. I find that as there is more uncertainty related to exploiting a given opportunity, investment professionals are more likely to share the competitive knowledge that went into analyzing and identifying the opportunity.

In Chapter 2, "From Audience to Evaluator: The Effect of Social Influence on Opt-in Evaluation Processes," I examine the rating stage of the evaluation process to understand the conditions under which potential evaluators opt to provide a rating. Specifically, I examine whether exposure to ratings from previous evaluators affects the likelihood of subsequent ratings occurring and the subsequent observed rating. Although prior research consistently shows that ratings significantly influence the attention an offering receives and its success, it is unclear whether exposure to prior ratings affects the likelihood that subsequent ratings occur or the subsequent ratings themselves. A major challenge in addressing this research question is identifying the set of actors who are at risk of rating an offering in the first place, namely the audience from which evaluators emerge. I was able to collect detailed investment-professional-level activity on RIC; therefore, I observe the entire evaluation process for each recommendation. Further, I am able to leverage a natural experiment related to exposure of audience members to average ratings from previous evaluators to causally identify the effect of social influence. I find that while social influence affects the likelihood of subsequent ratings, this effect is heterogeneous with respect to the valence of available ratings, and that conformity is the driving mechanism.

In Chapter 3, "Pursuing Quality: How Search Costs and Uncertainty Magnify Gender-based Double Standards in a Multistage Evaluation Process," with my coauthor Mabel Abraham, I examine the extent to which gender bias exists in a multistage evaluation process where objective quality information, related to performance, is freely available to evaluators. Because there is a visible market-based performance metric assigned to each recommendation and investment professionals are motivated to identify the most lucrative recommendations in this setting, we would not expect gender to be factored into this evaluation process. However, we find that recommendations posted by women are less likely to be selected (clicked-on in the first stage of evaluation) than similarly performing recommendations posted by men. We find this observed gender difference to be driven by uncertainty and search costs. The gender penalty is only present in the first stage of evaluation, where evaluators are selecting which recommendation to click on and view with limited information; in the second stage of evaluation, where evaluators have access to the analysis that supports the recommendation (available conditional on clicking on the recommendation), men and women receive comparable ratings. Furthermore, our results suggest that the female disadvantage in the first stage is most prevalent when evaluators are selecting recommendations from a large set of options and thus search costs are higher.

Chapter 1

Here's an Opportunity: Knowledge Sharing among Competitors as a Response to Uncertainty

1.1 Introduction

Organizations strategically foster knowledge sharing among their employees to improve key organizational outcomes (Argote 2012; Reagans and McEvily 2008; Zander and Kogut 1995). In recent years, an increasing number of firms have institutionalized this sharing by creating knowledge-sharing platforms *within* the organization (Hwang, Singh, and Argote 2015; McKinsey & Company 2013). However, a more puzzling form of knowledge sharing is also occurring, *across* an industry among competitors (e.g., Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Ingram and Roberts 2000; Schrader 1991; Zuckerman and Sgourev 2006). In addition to the general costs of knowledge sharing, such that it is time consuming and does not guarantee a positive return *ex ante*, knowledge sharing among competitors introduces a strategic cost: the potential loss of competitive advantage.

Organization and strategy scholars have posited that this type of sharing, among competitors, is most apt to occur when there is a pre-existing relationship between those sharing, when there is an expectation of direct reciprocity between those sharing, or when those sharing are in a slow-moving industry. The presence of these conditions is thought to attenuate the costs related to knowledge sharing, thus facilitating exchange (Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Ingram and Roberts 2000; Schrader 1991). Recently, however, there have been prominent examples of competitors coming together on a common platform to share knowledge (e.g., Towers Watson 2012; Value Investing Congress 2014b), and of firms openly sharing their knowledge with others in their industry (e.g., Tesla

Motors 2014). A major difference in these cases is that the knowledge sharing is much broader, whereby an actor shares with an audience, as opposed to the more dyadic sharing that is characterized in extant research. Moreover, in these contexts, technology is fast moving, and those sharing have little to no control over who has access to this knowledge. Thus, there is a gap in our understanding of the conditions that help sustain these instances of knowledge sharing among competitors.

In this study, I explain this form of sharing by focusing on how market uncertainty motivates resource-constrained entrepreneurs to engage in knowledge sharing with their competitors. An entrepreneur's goal is to identify and exploit opportunities (see Alvarez, Barney, and Anderson 2012 for a recent discussion; Casson 1982; Kirzner 1997; Knight 1921; Ricardo 1966); however, an opportunity can only be fully exploited if resource holders coordinate around the opportunity by committing their resources to it. Market uncertainty plays an important role in the opportunity exploitation process. It not only increases the stock of potential opportunities to be exploited (Knight 1921; Venkatraman 1997) but also introduces challenges and difficulties when a resource holder is attempting to evaluate an opportunity (cf. Podolny 1993; Stuart, Hoang, and Hybels 1999), which hinders the coordination process. I posit that in markets where there are positive externalities to coordinating with competitors around the same opportunity, knowledge sharing is a strategic response to high levels of market uncertainty aimed at facilitating this coordination process. In other words, competitors are willing to incur the costs associated with knowledge sharing when market uncertainty is heightened, in an effort to achieve successful coordination and subsequent opportunity exploitation. Positive externalities resulting from the presence of and coordination among competitors is not unique to the knowledge-sharing context (e.g., Barnett and Carroll 1987; Carroll and Hannan 2000; Ingram and Inman 1996; Sorenson and Audia

2000). However, we do not understand how competitors may act strategically, such as engaging in knowledge sharing, in order to facilitate this coordination.

I test this theory using a unique data set of knowledge sharing among "buy-side" (i.e., hedge fund, mutual fund) investment professionals who are members of an online knowledge-sharing platform, the Real Investors Club (a pseudonym). On this platform, investment professionals submit investment recommendations (to buy or short sell a stock) regarding a potential investment opportunity they have identified (i.e., that a stock is under- or over-priced). When they submit a recommendation, they must supplement it with a justification, which is visible to all current and future investment professionals on the platform. The accompanying justification must be either detailed, of a *minimum* of 600 words (averaging over 1,400 words), or simple, of a *maximum* of 40 words (averaging 24 words). I analyze how the likelihood of knowledge sharing, defined as utilizing a detailed justification, as opposed to a simple justification, is affected by market uncertainty, measured as the level of scrutiny and evaluation that a focal firm/stock faces from key market institutions (e.g., the media, sell-side analysts). This variation in knowledge sharing is important methodologically because it reduces measurement error that may result from selecting on cases of knowledge sharing without a baseline, or from relying on self-reported accounts. In this context the detailed justification represents clear instances of knowledge sharing, as investment professionals are detailing aspects of their thought and valuation process (their analysis) for investing in a stock, which is a large part of their competitive advantage. This stands in stark contrast to the simple justification, where investment professionals instead offer a short statement of support, with no accompanying rigorous analysis.

This study offers three main contributions to the literature on organizations and strategy. First, it provides the conditions that sustain these recent and broader examples of knowledge sharing among competitors: specifically, that knowledge sharing serves as a strategic response to market uncertainty in an attempt to coordinate with competitors. This finding also builds on other organization and strategy research that has highlighted the positive externalities stemming from the presence of and coordination among competitors (e.g., Barnett and Carroll 1987; Carroll and Hannan 2000; Ingram and Inman 1996; Sorenson and Audia 2000) by highlighting how competitors may act strategically to facilitate this coordination. Second, the context under study highlights the emergence of a new organizational form, which will have important implications for organizations. Although firms are increasingly utilizing within-firm online knowledge-sharing platforms, there may be limits within this environment, leading to the emergence of a new organizational form (Hannan, Pólos, and Carroll 2007; Kimberly 1979; Romanelli 1991; Stinchcombe 1965): platforms for interorganizational knowledge sharing. Third, these results have implications for economic sociologists studying the social structure of financial markets (Baker 1984; Beunza, Hardie, and MacKenzie 2006; MacKenzie and Millo 2003), as well as for developing a better understanding of market efficiency (cf. Zuckerman 2012). The existence of such platforms in the investment industry stands in direct contrast to the expectations of neoclassical finance and the efficient-market hypothesis (Fama 1965; Fama 1970).

1.2 Conditions Sustaining Knowledge Sharing among Competitors

Organizations promote knowledge sharing among their employees to improve key organizational outcomes (Argote 2012; Hansen 1999; Reagans and McEvily 2008; Zander and Kogut 1995). This has led to organizations institutionalizing this sharing by creating platforms *within* the firm that employees can use to share knowledge (Hwang, Singh, and Argote 2015; McKinsey & Company 2013). More paradoxically, this quest for knowledge has also resulted in knowledge sharing *across* an industry, among competitors. Although knowledge sharing—regardless of the relationship among the actors—is not costless, as there is a potential for lost time and an uncertain return *ex ante*, knowledge sharing among competitors introduces an added cost: the potential loss of competitive advantage (e.g., Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Ingram and Roberts 2000; Schrader 1991; cf. Zuckerman and Sgourev 2006).

At one end of the spectrum, similar organizations that operate in different geographic markets, and therefore compete for different consumer bases, have been found to openly share knowledge with one another (e.g., Zuckerman and Sgourev 2006). In this case, the loss of competitive advantage is mitigated by geographical dispersion, and these firms benefit from having their employees discuss and refine their strategy and best practices. However, knowledge sharing has also been found to exist between those who more directly compete with one another, where the loss of competitive advantage is salient. Studies examining this sharing among direct competitors have suggested that the costs related to this knowledge sharing are reduced when there is a pre-existing relationship between those sharing, when there is an expectation of direct reciprocity, or when the competitors are in a slow-moving industry (Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Schrader 1991; Stein 2008).

A pre-existing relationship between those sharing fosters trust and provides a vehicle for social sanctioning, thereby reducing informational frictions (Coleman 1988; Greif 1993; Ingram and Roberts 2000; Stiglitz 1990). Direct reciprocity, the expectation that an actor A shares with another actor B because A expects that B will initiate sharing in the future, mitigates the risk of uncertain return (Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Schrader 1991; Stein 2008). The distinction between direct reciprocity, as opposed to generalized reciprocity (e.g., Kollock 1999), is important. Direct reciprocity helps guarantee that no single actor receives a disproportionate benefit relative to the cost they incur within a given exchange relationship (i.e., it prevents a free rider problem). Finally, a slow-moving industry ensures that it would be difficult to implement the knowledge shared, hence protecting the sharer's competitive advantage (Appleyard 1996).

However, these factors fail to completely account for interorganizational knowledge sharing, where platforms have emerged to broadly connect competitors in order to facilitate knowledge sharing. An example of such a platform is the Value Investing Congress (VIC). Founded in 2004, the VIC is a biannual conference that brings together value investors with the straightforward mission of "providing delegates with immediately actionable investment recommendations...[and] helping attendees acquire the wisdom they need to understand and profit in the often-irrational market" (Value Investing Congress 2014b). One investment professional, reflecting on the conference, stated, "When I attend the [VIC], I know that I will go home with a ton of great investment recommendations and some new ways of viewing value investing" (Value Investing Congress 2014a). Here, an investment professional can attend and gain valuable strategic insights without having a pre-existing relationship or being expected to directly reciprocate with those sharing their knowledge. Further, those sharing knowledge are doing so with an audience of others, which is much different from the actor-to-actor exchange highlighted in previous research.

These platforms should also be of special interest to organization and strategy scholars: not only do they represent knowledge sharing among competitors outside the conditions previously outlined, but also they may represent a new organizational form (Hannan, Pólos, and Carroll 2007; Kimberly 1979; Romanelli 1991; Stinchcombe 1965). Specifically, there are limitations to the amount of novel information that exists within the firm. Knowledge-sharing platforms serve as a response to these constraints in the knowledge-sharing environment within the firm. Therefore, to better understand this organizational form it is imperative to identify the conditions that help sustain knowledge sharing among competitors in these contexts.

1.3 Knowledge Sharing among Competitors: Opportunity Exploitation, Coordination, and Market Uncertainty

Entrepreneurs (individuals or firms) search for opportunities within their market in order to exploit them and realize a return, or economic profit, from this discovery (see Alvarez, Barney, and Anderson 2012 for a recent discussion; Casson 1982; Kirzner 1997; Knight 1921; Ricardo 1966). On average, entrepreneurs are resource constrained, and therefore they cannot alone fully exploit a potential opportunity that they have discovered. Moreover, they rely on other resource holders coordinating around the opportunity; this coordination process is not automatic, however. When presented with an opportunity, resource holders must recognize that it is worth pursuing and then commit their resources to it (Shane and Stuart 2002: 155). If an entrepreneur can successfully coordinate resource holders around a given opportunity, the likelihood that the focal entrepreneur can fully exploit it increases.

A key factor affecting the identification of an opportunity and its exploitation is uncertainty: the probability of a given outcome cannot be known *ex ante* (Knight 1921). This market uncertainty stems from a disagreement about potential opportunities and the future returns they will generate. Market uncertainty serves as a double-edged sword. On one hand, without market uncertainty there could not be entrepreneurship. The cost of resources needed to exploit an opportunity would equal the opportunity's future value, nullifying a return to opportunity discovery (Barney 1986; Dierickx and Cool 1989). Hence, market uncertainty creates imperfections within the market, which increases the stock of potential opportunities available to exploit (Venkatraman 1997). On the other hand, heightened market uncertainty makes identifying an opportunity more difficult, which, most importantly, affects the flow of resources: they do not neatly flow to good opportunities while avoiding bad opportunities along the way. As market uncertainty increases, a resource holder's ability to evaluate the quality of an entrepreneur's potential opportunity is hindered (Podolny 1993; Stuart, Hoang, and Hybels 1999). Therefore, entrepreneurs may have to intervene in the coordination process; specifically, they may have to overtly attempt to coordinate resource holders around their opportunity.

One way that an entrepreneur can intervene in this process is by seeking out resource holders and sharing knowledge about their opportunity in an attempt to facilitate the coordination process. Traditionally, the entrepreneur–resource holder relationship is straightforward in this regard. For example, a main function of venture capital (VC) firms is to meet with entrepreneurs to discuss their opportunities and, if the VC is convinced of an opportunity's merit, to provide resources, such as capital and monitoring (e.g., Gompers 1995), increasing the likelihood that the opportunity is fully exploited.

Resource holders, however, are not always non-competing entities, and evidence suggests that the presence of and coordination among competitors generates positive externalities (e.g., Barnett and Carroll 1987; Carroll and Hannan 2000; Ingram and Inman 1996; Sorenson and Audia 2000). For example, even though firms face stronger competition from their local competitors, which leads to a higher likelihood of failure (Carroll and Wade 1991; Hannan and Carroll 1992; Ingram and Inman 1996), geographical agglomeration of similar firms is quite common (Krugman 1991; Saxenian 1996). In some cases, this coordination around a location is due to "natural advantages"; firms in the U.S. wine industry, for example, are mostly located in states where grape growing is easiest due to the cost advantages of being located near raw materials (Ellison and Glaeser 1999). However, a substantial proportion of agglomeration cannot be explained by these natural advantages (Ellison and Glaeser 1999). Sorenson and Audia (2000) explore this counterintuitive phenomenon and find evidence, in the shoe industry, that firms agglomerate in order to receive benefits related to knowledge and social capital from nearby competitors. Therefore, in these cases, entrepreneurs incur the costs related to coordinating around a similar location (e.g., higher failure rates) in order to extract benefits.

Benefits resulting from competitors acting in parallel can also be seen in other contexts, such as the financial markets. For example, if a resource-constrained investment professional finds an underpriced stock—an opportunity in the market—her next action is seemingly straightforward. She can commit her resources to this opportunity (i.e., buy the stock), and wait for other entrepreneurs to coordinate around this opportunity, committing their own resources. However, as uncertainty within the market for this opportunity increases, this process could take longer, and it is even possible that other entrepreneurs will fail to recognize this potential opportunity altogether. Accordingly, research on bubbles in the financial market underscores how these market inefficiencies can persist for long periods of time (Baker 1984; Brunnermeier 2009; Ofek and Richardson 2003; Shiller 2005; Temin and Voth 2004; Turco and Zuckerman 2014). Although evidence suggests that competitors can realize positive externalities from one another, we do not understand how competitors may act strategically, such as engaging in knowledge sharing, in order to facilitate this coordination.

A recent example elucidating knowledge sharing in an effort to facilitate coordination involves Tesla Motors. Initially, Tesla patented the technology that was related to the opportunities they discovered in their market, in order to maximize their realized return related to this discovery—the company held more than 1,400 patents by 2014 (Voyles 2014). The patent process is expensive, but, at the time, Tesla's management believed that the benefits of patenting outweighed the associated costs. However, Tesla recently announced that it was abandoning this strategy and would instead share this previously patented knowledge with its competitors in the auto manufacturing industry (Tesla Motors 2014).

Tesla's founder and CEO, Elon Musk, stated that "Tesla, other companies making electric cars, and the world would all benefit from a common, rapidly-evolving technology platform" and that this knowledge sharing would "strengthen rather than diminish Tesla's position" (Tesla Motors 2014). This quote from Musk highlights a prosocial goal; however, this overt attempt at motivating others to coordinate around their opportunities allows Tesla to realize a return from sharing this knowledge. This is evidenced by the fact that this strategic knowledge sharing quickly led to partnership discussions with rivals in the industry (Vance 2014) and an increase in Tesla's stock price (Voyles 2014), suggesting a positive return to such sharing.

I posit that in markets where there are positive externalities from competitors coordinating around the same opportunity, knowledge sharing serves as a strategic response to high levels of market uncertainty aimed at facilitating this coordination process. By sharing the knowledge that led to the discovery of an opportunity, entrepreneurs attempt to resolve market uncertainty and overtly focus the attention of their competitors (i.e., facilitate coordinating among other resource holders). It is not the case that opportunities do not exist when there are low levels of market uncertainty. However, under such conditions, other entrepreneurs are more likely to agree that an opportunity is present and to commit their resources naturally and in a timely fashion. Therefore, there is less need for intervention in the coordination process, reducing the likelihood that an entrepreneur will incur the costs of knowledge sharing with their competitors.

Hypothesis 1: *Conditional on identifying an opportunity within the market, an entrepreneur is more likely to engage in knowledge sharing with competitors when there is a high level of market uncertainty surrounding the opportunity.*

Targeting competitors when sharing knowledge offers various important benefits to the sharer. Specifically, though high levels of market uncertainty increases the likelihood that these competitors will miss an opportunity, they have sufficient absorptive capacity to grasp the opportunity and assess its merits when it is presented to them (cf. W. M. Cohen and

Levinthal 1990). Most importantly, if these competitors come to agree that this opportunity is worth pursuing, they also have the ability to commit their resources to it, which will increase the likelihood that it can be successfully exploited. It is difficult to empirically test whether facilitating coordination among competitors is a primary goal of knowledge sharing. However, if it is, knowledge sharing should be more likely when a failure to coordinate results in an entrepreneur incurring significant costs.

Generally, an entrepreneur who does not attract the necessary resources to their opportunity is less likely to exploit it and realize a profit from their opportunity discovery. However, in some cases, an entrepreneur has already incurred large costs related to their opportunity *ex ante*; therefore, achieving coordination is especially critical. For example, an entrepreneur may have already committed a significant amount of their own resources, such as capital and time, to an opportunity. If other resource holders do not coordinate around the opportunity in a timely manner, this entrepreneur will incur a large cost. Specifically, returning to the example of Tesla Motors, the costs associated with its failure to achieve coordination are much greater than that of an entrepreneur who has identified a potential opportunity but has not yet committed a significant proportion of their resources to it.

Hypothesis 2: *Conditional on identifying an opportunity within the market, if a primary goal of knowledge sharing is to facilitate coordination, than an entrepreneur is more likely to engage in knowledge sharing with competitors if there are greater costs associated with failing to coordinate.*

1.4 Empirical Context

The setting for this research was the Real Investors Club (RIC, a pseudonym), a private online platform that brings together buy-side (e.g., hedge fund, mutual fund) investment professionals (entrepreneurs) with the goal of openly sharing investment recommendations (opportunities) for individual securities (e.g., common stock). Buy-side investment professionals analyze securities with the goal of investing in them on behalf of their firm; sell-side analysts, on the other hand, analyze securities with the goal of disseminating their opinion to a client base (e.g., retail investors). In this way, buy-side investment professionals fall under the broad definition of entrepreneur: an actor who searches the market for opportunities in order to exploit them to realize an economic profit (see Alvarez, Barney, and Anderson 2012 for a recent discussion; Casson 1982; Kirzner 1997; Knight 1921; Ricardo 1966). Prospective members of RIC must apply for entry, and basic information about each investment professional, such as name and place of employment, is visible to other investment professionals on the platform.

The investment recommendations submitted on RIC focus on identifying current market opportunities rather than on discussing previous opportunities that worked out either well or poorly. When an investment professional submits a recommendation for a firm/stock,[1] they must include certain basic information: a recommendation (e.g., buy or sell); a price target, the price they expect the stock to reach; and an investment horizon, the estimated time for this price target to be reached (e.g., one year). They must also include a justification for this recommendation, which is visible to all current and future investment professionals on the platform. The accompanying justification must be either detailed, thoroughly discussing the analysis leading to the recommendation, *at least* 600 words long (averaging over 1,400 words), or simple, a statement supporting the recommendation, *at most* 40 words long (averaging 24 words). The content included in a detailed justification is monitored by RIC to ensure a minimal level of quality and rigor; however, the content of the simple justification is not strictly monitored, other than the 40-word limit.

[1] A stock refers to the shares that are issued by a publicly traded firm. Therefore, while "stock" is the term commonly used in this industry, the analysis is of the firm that the stock represents. I use both "stock" and "firm."

To supplement the data from RIC, I conducted 21 unstructured interviews with investment professionals, 12 of whom were members of RIC. These interviews provided more-detailed information about the investment industry. When asked what led them to join RIC, or another knowledge-sharing platform in the industry, interviewees almost always said that they wished to be part of a community of professional value investors. This elucidates their desire to have a broad audience with which to share their opportunities and knowledge. Interviewees also expressed gratitude to the community, stating that the investment recommendations on the platform affected their own view of their portfolio and their investment strategy, and that the feedback they received on their recommendations helped them hone their skills. Junior-level investment professionals noted that they discussed their desire to join a knowledge-sharing platform with their firm's management, suggesting that this was an organization-level decision. Those interviewed who were not part of at least one knowledge-sharing platform gave two common reasons for their lack of participation. First, some specified that their firm did not allow the analysis that led to their investments to be shared outside the firm (i.e., the content of a detailed justification). A Director of Research stated that it was important to his firm to keep this type of information away from competing firms. Similarly, one investment professional stated that they had to discontinue their use of knowledge-sharing platforms when they changed employers. Second, some investment professionals viewed their knowledge as too valuable to share. For example, a portfolio manager at a mutual fund specified that he would not want to advance someone else's career by allowing them to use his analysis. However, similar to those surveyed by Shiller and Pound (1989), these investment professionals stated that they engaged in knowledge sharing with a select few friends (i.e., pre-existing ties), where direct reciprocity was expected (see also L. Cohen, Frazzini, and Malloy 2008; Duflo and Saez 2002; Duflo and Saez 2003; Hong, Kubik, and Stein 2004; Hong, Kubik, and Stein 2005).

1.5 Data

The data for this study were all of the submitted investment recommendations for common stock—as opposed to debt or options—listed on a U.S. exchange (e.g., NASDAQ and NYSE) between 2008 and 2013 on RIC. This sample included 19,093 recommendations by 4,521 investment professionals. Of this total, 4,026 recommendations (about 21 percent) were submitted with a detailed justification. These data from RIC were supplemented with data about the firms/stocks featured in the recommendation. Financial market data came from the Center for Research in Security Prices (CRSP); sell-side analyst coverage data came from I/B/E/S; institutional ownership data came from Thomson-Reuters Institutional Holdings (13F) Database; and industry data came from Compustat.

To be included in the sample, the CRSP database had to cover the stock being recommended at least on the day before the recommendation was submitted. CRSP covers the major U.S. exchanges (e.g., NASDAQ and NYSE); therefore, it does not include data on stocks that trade via the over-the-counter (OTC) Bulletin Board. Most of the stocks on the OTC Bulletin Board are "penny stocks," which are characterized by their volatility as well as market uncertainty (see Ang, Shtauber, and Tetlock 2013 for a discussion), resulting in a conservative sample given the goals of this study.

1.5.1 Knowledge Sharing

The main dependent variable in this study was the indicator variable *Knowledge Sharing*, which took the value of 1 for an investment recommendation that was submitted with a detailed justification and 0 if a simple justification was utilized. While *some* information is being shared in simple justifications, it stands in stark contrast to the knowledge included in detailed justifications. Simple justifications are limited to 40 words, and average only 24 words, which severely constrains the ability to convey any meaningful knowledge or analysis about a given opportunity. Moreover, these simple justifications offer tenuous insight into the analysis that led to the specific recommendation (Figure 1). However, it could be argued that gauging another investment professional's absolute sentiment about a stock (buy versus sell) is useful; however, much these data are publicly available. For example, the Securities and Exchange Commission (SEC) requires all mutual funds to report their complete list of holdings each quarter (through Forms N-Q and N-CSR), and the SEC requires other institutional investors (e.g., hedge funds) with more than $100 million in equity assets under management to report their holdings quarterly via Form 13F.

[Figure 1]

On the contrary, detailed justifications offer valuable insights about how an investment professional thought about a particular investment opportunity and the analysis that supported this recommendation. The content of detailed justifications commonly includes an analysis of supporting information, gleaned from meetings with management (and investor calls), recent news, and company reports (e.g., quarterly filing—10Q); comparable companies, such as competitors; macroeconomic and industry trends; and the valuation. Therefore, a detailed justification, relative to a simple justification, offers a rigorous level of both qualitative and quantitative knowledge. Interviewees often mentioned that these justifications took months to research and hours to create; one said that it took him more than 12 hours to complete. Further, one investment professional stated that the detailed justifications he submitted to RIC were identical to the proposals he submitted internally to his portfolio manager. This indicates that the knowledge included in a detailed justification is much closer to the firm-level strategic knowledge.

To further elucidate why a detailed justification represents knowledge sharing and a simple justification does not, let's return to the portfolio manager from above who refused to share knowledge because he did not want someone else using his analysis. He was not opposed to others knowing the stocks he was invested in—his portfolio is a matter of public record (through SEC regulations). What he wished to safeguard was the analysis that led to his identifying a given market opportunity—the knowledge contained in a detailed justification. When asked about the differences between using the simple and the detailed justifications, an investment professional said, "I see them as two completely different vehicles, [the detailed justification] lets me fix the market by sharing my due diligence with the community while [the simple justification] lets me make a call." The "fix[ing]" of the market speaks directly to the strategic use of knowledge sharing: an investment professional who finds an opportunity, but who faces high levels of market uncertainty, is motivated to engage in knowledge sharing with competitors to combat this uncertainty and facilitate the coordination process. Importantly, this "fix[ing]" reflects the investment professional's belief that he or she has identified a market opportunity, and not an altruistic desire to make the market efficient. The motivation for utilizing a simple justification was less clear. Those who were interviewed were in agreement with the above quote, regarding simple justifications as "mak[ing] a call." In other words, they valued being able to prove that they had identified an opportunity. This suggests that investment professionals utilized simple justifications when they had less need to facilitate the coordination with other investment professionals. Importantly, the platform does not guide investment professionals to use one type of justification over another—members are free to select a justification type.

The ability to leverage variation in knowledge sharing within the same context is important methodologically. Previous research has often focused on cases of knowledge sharing and then highlighted the conditions that were simultaneously present or has relied on self-reports of knowledge-sharing activities (e.g., Appleyard 1996; Fauchart and von Hippel 2008; von Hippel 1987; Ingram and Roberts 2000; Schrader 1991). While this research has shed important light on the phenomenon of knowledge sharing among competitors, this method of analysis introduces the possibility of measurement error. The stark variation between these types of justification in my context allows for the use of an appropriate baseline. Namely, this variation in knowledge sharing allows for an analysis between recommendations with knowledge sharing and recommendations without knowledge sharing (see Fernandez and Sosa 2005 for a similar discussion related to labor market research)—conditional on joining RIC.

1.5.2 Market Uncertainty

Market uncertainty was captured using multiple measures related to the level of scrutiny and evaluation a firm/stock faced from key market institutions, which has been shown to affect the expected uncertainty within the market for a stock (Boehmer and Kelley 2009; Fang and Peress 2009; Yu 2008; Zhang 2006). The goal of this approach is to not overemphasize the coefficient of any one measure but instead to interpret the results collectively. Specifically, the following measures were used: *Firm Age*, *Sell-Side Coverage*, *Institutional Ownership Concentration*, and *Media Coverage*.

Firm Age was calculated as the difference between the year the investment recommendation was submitted and the initial year the stock was covered in the CRSP database (most often the firm's IPO year), plus 1. *Firm Age* approximates the availability of historical data—an overall sense of information availability—for a firm. As time passes there is more information and certainty about a firm's strategy, leadership, and performance. Additionally, given that these are public firms, "older" firms have also submitted more financial documentation (e.g., quarterly reports) to the SEC.

Sell-Side Coverage was calculated as the sum of the number of unique earnings estimates for the stock featured in the investment recommendation, in each of the four quarters prior to that recommendation. When a firm becomes publicly traded on a U.S. exchange, sell-side analysts may choose to initiate coverage of the firm. This set of sell-side analysts will issue periodic reports about the firm/stock. These reports routinely include historical information, industry outlooks, earnings estimates, and other analyses. As this coverage increases, so does scrutiny of the firm, and information about the firm reaches a wider audience. Greater coverage has been found to be directly related to a firm's information availability and to increases in price for underpriced stocks (e.g., Bushman, Piotroski, and Smith 2005; Bushman and Smith 2001; Francis, Douglas Hanna, and Philbrick 1997; Lang and Lundholm 1996), and this increased level of scrutiny leads to beneficial outcomes in terms of corporate governance (Yu 2008). For this measure, if three unique analysts covered a stock in each of the last four quarters (3*4 = 12), and two additional analysts cover the stock, but for only two of the last four quarters (2*2 = 4), *Sell-Side Coverage* would take the value of 16 (12+4). If estimates were updated within a given quarter, *Sell-Side Coverage* was not changed.

Institutional ownership is calculated as the ratio of the number of shares of a firm's stock owned by institutional investors that file Form 13F to the total number of shares outstanding. Institutional investors may include banks, hedge funds, mutual funds, pensions, or endowments. These are investment professionals that manage money for their clients. Given their large pool of capital for investment, institutional investors can take large investment positions in a firm, which gives them substantial influence over management practices, such as aligning compensation with shareholder expectations (e.g., Connelly et al. 2010; David, Kochhar, and Levitas 1998) and promoting long-term innovation efforts (e.g., Kochhar and David 1996). The number of institutional investors, as well as the number of shares an institutional investor owns of a firm, varies greatly; therefore, recent research has focused on the concentration of institutional ownership. Empirical evidence suggests that when institutional ownership is concentrated among fewer institutional investors, there is more uncertainty in the price–value relationship for that stock (Boehmer and Kelley 2009).

Following this research, I dichotomized institutional ownership[2] into two separate variables, *Institutional Investor Concentration (Percent, Top 5)* and *Institutional Investor Concentration (Percent, Other)*, for each firm in the quarter preceding the investment recommendation

To better understand the construction of these two variables, let's consider, for example, *Firm A* that has a total of 100 shares outstanding and has seven institutional investors, with the sum of the shares they each independently own being 80. First, a rank order is created of how many shares of *Firm A*'s stock are owned by each of the seven institutional investors. *Institutional Investor Concentration (Percent, Top 5)* is calculated as the ratio of the sum of shares of *Firm A*'s stock that are owned by each of the five (of the seven) largest institutional investors to the total number of shares of *Firm A*'s stock outstanding (here, 100). *Institutional Investor Concentration (Percent, Other)* is calculated as the ratio of the total number of shares of *Firm A*'s stock that are owned by the remaining firms (here, two) to the total number of shares of *Firm A*'s stock outstanding (here, 100). Therefore, if the five largest institutional investors collectively owned 60 shares, *Institutional Investor Concentration (Percent, Top 5)* would take the value of 0.60 (60/100), whereas *Institutional Investor Concentration (Percent, Other)* would take the value of 0.20 ((80-60)/100). For firms/stocks that had between one and five institutional investors, *Institutional Investor Concentration (Percent, Other)* would take the value of 0.

Media Attention was measured as the number of articles in which a firm/stock was discussed, in the month preceding the investment recommendation, plus 1. These counts were hand collected from a leading website focused on financial markets that aggregates and publishes news about firms/stocks. A greater amount of media attention implies that a firm

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[2] There are instances in which institutional ownership is reported as exceeding 100 percent. As discussed by Asquith and colleagues (2005), there are legitimate reasons for this counterintuitive result. In this sample, institutional ownership was capped at 100 percent. Results are robust to the removal of these observations.

faces a higher level of scrutiny and evaluation. Similarly, media coverage has been found to affect a firm's stock price, even when no genuine news is supplied (Fang and Peress 2009). Further, substantial (even unrelated) media coverage in a previous period has been found to attenuate the effect of negative future events, such as protests, on stock returns (King and Soule 2007).

For these measures, besides the institutional ownership concentration variables, market uncertainty *decreases* as the value of these measures *increases*. Therefore, market uncertainty is maximized when the value of these measures, $\mathbf{X}$, is minimized. For consistency with the hypothesized relationships, the inverse of these measures, $(1/\mathbf{X})$, was used. To more concretely illustrate this transformation, consider the variable *Firm Age*. During a firm's first year, *Firm Age* is equal to 1 (0+1), with its inverse being 1/1, and after four more years *Firm Age* for this same firm is equal to 5 (4+1), with its inverse being 1/5. Since market uncertainty should be higher, *ceteris paribus*, for smaller values of *Firm Age* we would expect the values of *Firm Age* used in the analyses to correspond to this notion, i.e., $1/1 > 1/5$.

1.5.3 Coordination as a Goal of Knowledge Sharing

The variable Short Recommendation is a dichotomous variable that takes the value of 1 if the investment recommendation was to short sell the stock and a value of 0 if the recommendation was to buy and hold the stock. Short selling is a unique feature of the U.S. stock market; however, its presence allows for a test of the likelihood of sharing knowledge when there are greater costs associated with failing to coordinate (hypothesis 2). Short selling allows an investor who is pessimistic about the current price of a given stock (i.e., believes it to be overvalued) to borrow shares of a stock that they do not own, for a fee, and sell them back to the market. The investor agrees to return the shares at a later date, along with interest, and any distributions (e.g., dividends) that occur during the borrowing period. A short seller profits when a stock price decreases relative to when he borrowed the shares. While the availability of short selling is an important mechanism for an efficient market (Asquith et al. 2005, Curtis and Fargher 2014), it is frequently criticized because achieving coordination is especially necessary, relative to buying a stock (Abreu and Brunnermeier 2003, Brunnermeier and Nagel 2004). Unlike when buying a stock, an investor who short sells a stock does not own a piece of the firm and faces the possibility of infinite loss—there is no maximum on the price the stock could reach. Therefore, failing to coordinate with other resource holders is especially costly when short selling.

1.5.4 Control Variables

Variables at the investment-professional and investment-recommendation level were used as controls. At the investment-professional level, these measures included education, using a ranking of both undergraduate and graduate institution, and the investment professional's physical location. At the investment-recommendation level, investment horizon, firm size, industry fixed effects, and year fixed effects were included.

For undergraduate education, the *2013 US News College Ranking* (U.S. News & World Report 2014b) was used to match an investment professional's undergraduate institution to its ranking. This was also done for graduate education. For U.S. business schools the *2013 US News MBA Ranking* was used (U.S. News & World Report 2014a), and for non-U.S. business schools, the *2013 Financial Times Global MBA Ranking* (Financial Times 2014) was used. Institutions were grouped into four categories: *Top* ranked (under)graduate institution (for a ranking of 1-10), *Mid* ranked (under)graduate institution (for a ranking of 11-50), *Bottom* ranked (under)graduate institution (for a ranking of 51-100), and *Unranked* (under)graduate institution (for a ranking greater than 100 or missing). Investment professionals who did not self-report an undergraduate institution were coded as unranked. Additionally, the dichotomous variable *No Grad* was coded 1 if no graduate school was listed. Controlling for education is important because certain institutions may train investment professionals to act in a certain way with regard to sharing knowledge.

Given that an investment professional's city has been found to affect his or her investment choices (e.g., Hong, Lim, and Stein 2000) and available resources, location was included as a control. *Major City* represents large metropolitan cities in the U.S. that are often thought of as financial hubs (e.g., Boston, Chicago, New York City, San Francisco), and took the value of 1 for all investment professionals working in these cities. Additionally, the indicator variable *Non-US* took the value of 1 for all investment professionals located in a city outside of the U. S.

At the investment-recommendation level, certain firm sizes, investment horizons, industries, or time periods may be more suitable for knowledge sharing. *Firm Size* was calculated as the market capitalization (share price*shares outstanding) of the stock featured in the investment recommendation (in billions), on the day prior to the recommendation being submitted, using the shares outstanding reported in the previous quarter. Although firm size has been found to be correlated with measures related to market uncertainty for a stock (Atiase 1985; Fang and Peress 2009; Grant 1980), it also captures many other factors, making it a necessary control in all models. Similar to the above reasoning, the inverse of *Firm Size* was used in the analyses. An investment professional's investment horizon may affect her likelihood to engage in knowledge sharing; therefore, the indicator variable for recommendations of *Short Investment Horizon* took the value of 1 if the investment professional has an investment horizon of under one year. Additionally, industry and year fixed effects were included in all models. Table 1 provides summary statistics for each of the key variables, separated by justification type, and Table 2 provides correlations.

[Table 1]

[Table 2]

1.5.5 Empirical Model

I estimated the following logit regression to evaluate hypothesis 1:

$$\textit{Knowledge Sharing}_i = \beta_1 \textit{Measures of Market Uncertainty} + \gamma X_i + \delta_i + \lambda_i + \varepsilon_i,$$

where i indexes the investment recommendation, the unit of analysis. X_i is a vector of controls for recommendation i; δ_i is a fixed effect for the stock's industry in recommendation i and includes 24 two-digit North American Industry Classification System (NAICS) sectors, and an indicator for a missing NAICS sector; and λ_i is a fixed effect for the year recommendation i was submitted. Robust standard errors were clustered at the investment-professional level given the possibility that the choice of sharing knowledge and choosing which types of stock to analyze may be correlated within investment professional. To evaluate hypothesis 2, I estimated a similar logit regression. In this analysis, I introduced the indicator variable *Short Recommendation* to help explain the likelihood of knowledge sharing if a short-selling recommendation was submitted.

1.6 Results

Figure 2 presents evidence that investment professionals were more likely to share knowledge (i.e., utilize a detailed justification) when identifying opportunity related to smaller firms. The average market capitalization of a stock recommended with a detailed justification was approximately $6.8 billion, almost one-third the size of the average market capitalization of the stocks listed on the Standard & Poor's 500 (S&P 500; $19.1 billion, at the midpoint of the period under study). Without the existence of an alternative justification type, it would not be possible to distinguish between the following two explanations: that investment professionals share knowledge as a response to high levels of market uncertainty, or that investment professionals who share knowledge prefer stocks with high levels of market uncertainty. Comparing the market capitalization of the firms discussed across these two justifications—detailed versus simple—begins to adjudicate between these two possibilities

(Figure 2). From Figure 2, it is evident that there was a strong relationship between *Firm Size* and the likelihood of sharing knowledge. The average market capitalization of stocks recommended with a simple justification was about $18.4 billion, similar to that of the S&P 500, and approximately two and one-half times larger than that of stocks recommended with a detailed justification ($p < 0.001$).

[Figure 2]

To rigorously test hypothesis 1, I used proxies for market uncertainty, related to level of scrutiny and evaluation that a focal firm/stock faced—namely the inverse of *Sell-Side Coverage*, *Firm Age*, and *Media Attention*, as well as *Institutional Investor Concentration*. Overall, these results (Table 3) offer support for hypothesis 1, suggesting that at high levels of market uncertainty there was a greater likelihood of knowledge sharing. For example (Table 3, M2), the odds that an investment professional recommended a stock using a detailed justification are about 22 percent higher when the firm's/stock's *Sell-Side Coverage* is one standard deviation (44.99) below the mean (60.93) than at the mean (i.e., when fewer sell-side analysts are covering the stock), 1.307 (exp[(1/15.94)*4.267]) versus 1.073 (exp[(1/60.93)*4.267]). Similarly, the coefficient of *Firm Age* (Table 3, M3) suggests that the log odds that an investment recommendation for a stock that has recently IPO'ed involves knowledge sharing are higher than for a firm that has been public for several years. Moreover, when market uncertainty, measured by *Media Attention*, was high, there is an increase in the log odds that an investment professional engaged in knowledge sharing (Table 3, M4). The odds are 42 percenter higher that an investment professional shared knowledge when a firm/stock received the mean (1.65) amount of media attention versus when a firm/stock received media attention that was one standard deviation (7.18) above the mean, 1.538 (exp[(1/1.65)*0.710]) versus 1.084 (exp[(1/8.83)*0.710]).

[Table 3]

Market uncertainty measured by the concentration of institutional investors yielded a consistent result, with *Investor Concentration (Percent, Top 5)* strongly predicting the odds of knowledge sharing (Table 3, M5). The log odds of knowledge sharing were higher when there was a greater concentration of ownership among five or fewer institutional investors for a given stock. This effect was moderated as concentration increased outside of this small set of institutional investors, *Investor Concentration (Percent, Other)*, meaning institutional ownership was more dispersed. Overall, these results offer strong empirical support for hypothesis 1, that conditional on identifying an opportunity within the market, an investment professional is more likely to engage in knowledge sharing with his competitors when faced with high levels of market uncertainty.

A possible alternative explanation could be that these investment professionals need to provide more detail for the firms/stocks that face a lower level of scrutiny and evaluation from key market institutions because they are less well known. However, it is important to point out that the average recommendation that includes knowledge sharing focuses on a significant firm in the economy—one that with an average firm size of $6.8 billion, which is larger than the average firm size of those publicly on a U.S. exchange ($6.4 billion). Further, since all of the firms in my sample are publicly traded, they file financial statements and other key news with the SEC. Moreover, the average firm recommended with knowledge sharing in my sample had about 50 unique sell-side estimates in the four quarters prior to the recommendation. Therefore, these are not obscure firms, but there is a higher levels of market uncertainty at the time of the recommendation. This alternative also fails to explain: *what is the goal of this knowledge sharing?* What these investment professionals are doing is sharing knowledge by providing a rigorous analysis of these firms, which can take months to complete. This is the knowledge that supports the potential opportunity in an effort to motivate other resource holders to coordinate around the opportunity, thereby increasing the likelihood that it can be fully exploited. Conversely, opportunities still exist when there are lower levels of market uncertainty, however, other resource holders are more likely to naturally coordinate around the opportunity, making it less likely that an investment professional opts to incur the costs associated with knowledge sharing.

To test that the goal of knowledge sharing is to facilitate coordination, hypothesis 2 predicted a greater likelihood of knowledge sharing when the costs associated with failing to facilitate coordination around an opportunity are high. The measure, *Short Recommendation*, was used to proxy for such opportunities. Across all model specifications (Table 4), it is evident that the odds of knowledge sharing were significantly higher for short-selling recommendations than for buy-and-hold recommendations. On average, the odds that an investment recommendation involved knowledge sharing were between 1.685 (exp[0.522]) to 1.813 (exp[0.595]) times higher when a recommendation was to short sell a stock relative to buy-and-hold a stock.

[Table 4]

To further unpack this result, I included interactions between *Short Recommendation* and each measure of market uncertainty (Table 5). These results provide further evidence that knowledge sharing is most likely when there are greater costs from failing to coordinate, and that this pattern holds at all levels of market uncertainty. The only marginally significant interaction is between *Short Recommendation* and *Media Attention* (Table 5, M11; $p < 0.10$). This result is especially interesting given extant organizational research on the relationship between short selling and the media. Specifically, wider media coverage may shield a firm from negative events (King and Soule 2007). Therefore, since to exploit a short-selling opportunity the stock price must decrease, successfully inducing coordination around a short-selling opportunity may become especially difficult as media coverage increases. Note that the significant interaction between *Short Recommendation* and *Institutional Investor*

Concentration (Per., Other) is not surprising given the mechanics of short selling. In order to short sell a stock, an investor must borrow shares from a current shareholder, typically an institutional investor. Thus, as institutional investor concentration becomes more disperse, there is a greater supply of lenders available. These results provide support for hypothesis 2: knowledge sharing is more likely if there are greater costs associated with failing to achieve coordination from other resource holders. Further, the results of this interaction show how important the goal of coordination is for knowledge sharing. Even when there are low levels of market uncertainty, when the cost of failure to coordinate it high enough knowledge sharing can be supported.

[Table 5]

Overall, competitors incur the costs of knowledge sharing when they are faced with high levels of market uncertainty in an effort to facilitate coordination among other resource holders. If they are able to facilitate coordination around this opportunity, by mobilizing others to commit their capital, they increase the likelihood that they will successfully exploit the opportunity.

1.6.1 Ruling Out Within-Person Alternative Explanation

While simple justifications present an important baseline for analysis, it is still possible that selection into knowledge sharing is affecting the above results. Specifically, since there is no guidance for when an investment recommendation should include a detailed justification versus a simple justification, certain types of investment professionals may select into knowledge sharing. For example, some investment professionals may want more feedback on their investment process, which is more extensively available when a detailed justification is utilized, or they may be motivated by general reciprocity (Kollock 1999), altruism (e.g., Hsu and Lin 2008), or general career outcomes (e.g., Lakhani and Von Hippel 2003). Further, the above results may be driven by unobserved investment professional heterogeneity. Although these concerns would not exclude the above knowledge-sharing hypotheses, it would open the door to possible alternative explanations that stem from individual-level motivations.

To address this concern, I identified investment professionals who submitted at least one investment recommendation with a detailed justification and at least one recommendation with a simple justification. Individual fixed effects were then included in all models, allowing for a within-investment-professional analysis. The analyses presented in Table 3 were replicated in Table 6 and the analyses presented in Table 4 were replicated in Table 7, using this new sample and specification. These results are robust; evidence still strongly suggests that investment professionals are more likely to bear the costs of knowledge sharing when there are high levels of market uncertainty surrounding an opportunity in an effort to facilitate coordination among their competitors.

[Table 6]

[Table 7]

1.7 Discussion

Knowledge sharing is costly, it is time consuming and it does not guarantee a positive return *ex ante*, however, it occurs quite frequently in the economy. What is particularly surprising is that knowledge sharing even occurs among competitors because there is an added cost to this type of sharing: loss of competitive advantage. In this paper, I propose that in markets where positive externalities are generated from competitors acting in parallel, knowledge sharing serves as a strategic response to high levels of market uncertainty in an effort to facilitate coordination among competitors around a potential opportunity. A resource-constrained entrepreneur can only fully exploit an opportunity that they have discovered if they are able to coordinate other resource holders around it. Further, heightened market uncertainty makes identifying an opportunity more challenging, hindering the likelihood that resource holders will naturally coordinate around a given opportunity.

Therefore, an entrepreneur who faces high levels of market uncertainty is motivated to share the knowledge that led to the discovery of an opportunity in order to convince other resource holders (competitors) that the opportunity is present and that they should commit their resources to it. If this coordination effort succeeds, it is more likely that the opportunity will be fully exploited, offsetting the inherent costs of knowledge sharing among competitors. Leveraging data from an online knowledge-sharing platform for investment professionals, I find significant evidence in support of this theory.

While this study explains knowledge sharing in an important economic market, the financial market, and parallels cases in more traditional entrepreneurship, its explanatory power is limited by key scope conditions. The theory outlined above assumes that the market in question is one where actors are resource constrained; in other words, they cannot successfully exploit potential opportunities they have found without also strategically coordinating with other resource holders. The financial markets context is also well suited in terms of available measures of market uncertainty, which may be more difficult to identify in other industries.

This study offers three main contributions to the literature on organizations and strategy. First, it advances our understanding of knowledge sharing among competitors by identifying an additional condition under which this sharing is probable, namely when there are high levels of market uncertainty surrounding an opportunity. Unlike existing accounts of knowledge sharing, which have focused on more dyadic sharing, this study focuses on a different and emerging type of knowledge-sharing platform where actors share with a broader audience. Similarly, this research complements other organization and strategy studies that have provided evidence of positive externalities being generated from the presence of and coordination among competitors (e.g., Barnett and Carroll 1987, Ingram and Inman 1996, Sorenson and Audia 2000) by focusing on how competitors may act strategically in order to facilitate this coordination.

This new proposed condition for sustaining knowledge sharing among competitors does not invalidate previous conditions. Instead, it adds to this research to help explain a type of knowledge sharing not previously considered. Further, it is possible that these conditions also play a role in entry into these knowledge-sharing platforms. For example, we may expect that an actor is more likely to join a knowledge-sharing platform with competitors if similar firms allow their employees to join, or if an employee knows others on the platform. It is also expected that these individual-level motivations, such as receiving feedback, are a major driver for joining such platforms. Investment professionals that I interviewed stated that the feedback they received helped them in future opportunity recognition. This idea resonates with evidence from extant research on knowledge sharing within the firm or knowledge communities more broadly, where feedback is a major component of the knowledge-sharing process (Cummings 2004; Hansen 1999). As it pertains to this study, however, these motivations do not explain why investment professionals share knowledge about some opportunities they have identified but not others (Table 6 and Table 7). However, this leaves an opportunity for future work, such as developing a better understanding of how firms that allow their employees to join differ from those that do not.

Second, the main variables of this study relate to market uncertainty as measured by the level of scrutiny and evaluation that key market institutions provide. In most industries, there are often limits to what a firm can provide and what can effectively occur within a firm, creating a void in the environment and allowing for the introduction of new organizational forms (Hannan, Pólos, and Carroll 2007; Kimberly 1979; Romanelli 1991; Stinchcombe 1965). For example, Kimberly (1979) finds that limitations in the medical field, related to a shortage of doctors and field specialization, led to a new type of medical school. In the financial markets context under study, the organizations responsible for supplying this information and scrutiny are limited. For example, an investment bank cannot hire enough sell-side analysts to cover every individual stock that publicly trades on the stock market, which leads to coverage limits (cf. Zuckerman 1999). Similarly, the media are rewarded for viewership and readership; therefore, we should expect them to focus on firms that are prominent in the public view. This void in the environment stemming from the limitations of previous organizations may be responsible for the emergence of this new organizational form, one that facilitates knowledge sharing in order to deal with the market uncertainty and assists in opportunity exploitation.

This opens a wealth of research opportunities for organization and strategy scholars to better understand the emergence and sustainability of this new organizational form. My context is a specific type, but far from the only one in the investment industry or more broadly in other industries. For example, in the insurance industry a knowledge-sharing network was created to increase "peer networking and best practice educational opportunities" (Towers Watson 2012). Similar to my proposed theory, this effort focused on a broader audience: "While certain insurers already have forums available to them, the CRO Network is very inclusive, and provides networking and knowledge-sharing opportunities for virtually all insurers operating in North America" (Towers Watson 2012). Similarly, a fruitful direction for future research is to examine how market uncertainty with regard to opportunity recognition has affected the emergence of other organizational forms, such as crowd-funding ventures. Further, the richness of the data available from such platforms provides many opportunities to better understand the implications from the interactions that occurs within these platforms, such as receiving feedback.

Third, this study contributes to the work of economic sociologists who are especially interested in financial markets (Beunza, Hardie, and MacKenzie 2006; MacKenzie and Millo

2003; Turco and Zuckerman 2014; Zuckerman 2012). Specifically, the existence of such platforms in the investment industry stands in direct contrast to the expectations of neoclassical finance and the efficient-market hypothesis (EMH; Fama 1965; Fama 1970). These findings suggest that it is important to view the EMH as an ideal, and not as a perfect model for market outcomes. Although the existence of knowledge-sharing platforms in the investment industry does not invalidate the EMH, my findings suggest that it would be more productive for future research to explore how shortcomings in the EMH elicit (or suppress) market action.

Along this line of inquiry, this study shows that when reaching market efficiency is expected to face larger obstacles, market action may take an unexpected form. These findings contribute to other work in economic and organizational sociology that has attempted to move beyond classic models of the market to better understand market action and its implications more broadly (e.g., Baker 1984; Beunza, Hardie, and MacKenzie 2006; Granovetter 1985; Lounsbury and Hirsch 2010; MacKenzie and Millo 2003; Zuckerman 1999). For example, the open discussion of opportunities in financial markets among these investment professionals lends evidence to the idea of price as a "social thing" (Beunza, Hardie, and MacKenzie 2006) instead of a purely mechanical process. Further, these findings answer calls for scholars in fields other than just finance to discuss issues of market efficiency (Zuckerman 2012).

Knowledge-sharing platforms also have important practical implications at the organizational-level. Although some investment professionals who were interviewed stated that their firm viewed its internal knowledge as too valuable to share with competitors, this may be a shortsighted strategy. It is important to capture the value of opportunity discovery; however, coordination is often needed to fully exploit an opportunity. Therefore, these innovative knowledge-sharing platforms that connect competitors may have strategic value for realizing a return to opportunity discovery, especially when market uncertainty is high; therefore, firms should seriously consider engaging in them. Of course, this does not mean that entrepreneurs should race to tell their competitors every detail related to a potential opportunity; however, it does mean that entrepreneurs should consider the possible value of sharing some knowledge, under certain conditions. When a first-mover advantage is relatively protected, or in some cases less of an issue, these innovative platforms may serve as an integral part of organizational strategy going forward.

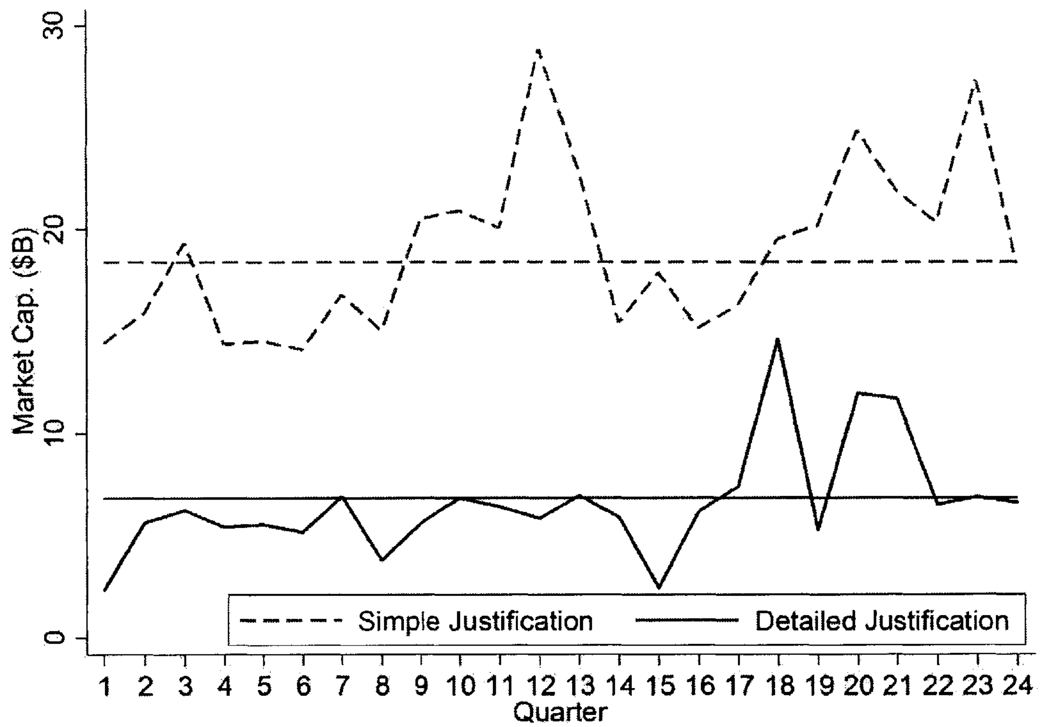
1.8 Figures and Tables

Figure 1: Sample of Simple Justifications

Others in the industry are trading at 14 times price-to-earnings. [Firm] is only trading at 10!
Poised for a bounce back after some bad luck with market conditions, plus offers a great dividend
With home building picking back up they should be able to capitalize
Exceptional company that is well placed in the market in terms of its top products. Looks good relative to competitors.
The entire industry is undervalued and [FIRM] has the highest upside.
There are some important risks to consider but if their drugs do not hit any snags in FDA approval this stock can easily triple. New CEO also is looking to grow the distribution channels.

Note: Each row is an example of a simple justification. This is a reproduction from actual data and removes any information about the firm/stock.

Figure 2: Average Market Capitalization of Recommendations by Justification Type



Note: Market capitalization averaged across investment recommendations within quarter and within justification type from 2008 to 2013. The horizontal lines represent the overall sample mean for the respective justification type.

Table 1: Summary Statistics of Key Variables

Panel A: Detailed Justifications

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Key Explanatory Variables					
Sell-Side Coverage[a]	3,538	50.204	41.225	4.000	272.000
Firm Age	4,026	16.653	17.424	0.000	88.000
Media Attention	4,026	1.269	7.175	0.000	183.000
Instit. Investor Concen. (Per., Top 5)[a]	3,552	0.288	0.132	0.002	1.000
Instit. Investor Concen. (Per., Other)[a]	3,552	0.364	0.205	0.000	0.778
Short Recommendation	4,026	0.161	0.367	0.000	1.000
Control Variables—Recommendation Level					
Firm Size (B)	4,026	6.828	29.232	0.006	594.864
Short Investment Horizon	4,026	0.425	0.494	0.000	1.000
Control Variables—Investment Professional Level					
Location: Major City	4,026	0.724	0.447	0.000	1.000
Location: Non-US	4,026	0.053	0.225	0.000	1.000
Education (Ref: Mid-Rank)					
Undergraduate Rank: Top	4,026	0.240	0.427	0.000	1.000
Undergraduate Rank: Bottom	4,026	0.110	0.313	0.000	1.000
Undergraduate Rank: Unranked	4,026	0.314	0.464	0.000	1.000
Graduate Rank: Top	4,026	0.275	0.447	0.000	1.000
Graduate Rank: Bottom	4,026	0.023	0.150	0.000	1.000
Graduate Rank: Unranked	4,026	0.036	0.185	0.000	1.000
Graduate Rank: No Grad.	4,026	0.571	0.495	0.000	1.000

Panel B: Simple Justifications

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Key Explanatory Variables					
Sell-Side Coverage[a]	13,824	63.673	45.497	4.000	272.000
Firm Age	15,067	19.115	19.160	0.000	88.000
Media Attention	15,067	1.747	7.172	0.000	147.000
Instit. Investor Concen. (Per., Top 5)[a]	13,337	0.276	0.124	0.000	1.000
Instit. Investor Concen. (Per., Other)[a]	13,337	0.408	0.185	0.000	0.812
Short Recommendation	15,067	0.053	0.223	0.000	1.000
Control Variables—Recommendation Level					
Firm Size (B)	15,067	18.357	47.490	0.002	657.975
Short Investment Horizon	15,067	0.127	0.333	0.000	1.000
Control Variables—Investment Professional Level					
Location: Major City	15,067	0.726	0.446	0.000	1.000
Location: Non-US	15,067	0.077	0.267	0.000	1.000
Education (Ref: Mid-Rank)					
Undergraduate Rank: Top	15,067	0.291	0.454	0.000	1.000
Undergraduate Rank: Bottom	15,067	0.090	0.286	0.000	1.000
Undergraduate Rank: Unranked	15,067	0.299	0.458	0.000	1.000
Graduate Rank: Top	15,067	0.273	0.446	0.000	1.000
Graduate Rank: Bottom	15,067	0.013	0.112	0.000	1.000
Graduate Rank: Unranked	15,067	0.020	0.139	0.000	1.000
Graduate Rank: No Grad.	15,067	0.620	0.485	0.000	1.000

Notes: This table compares summary statistics for recommendations that included a detailed justification (Panel A) to those that included a simple justification (Panel B).
[a]The number of observations for these measures is less than the maximum sample size because values for these measures were not available for all of the firms in the sample. Analyses using these measures treated these observations as missing for a more conservative test instead of 0. Results are robust to changing missing values to 0.

Table 2: Correlation of Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Sell-Side Coverage	1.000																
(2) Firm Age	0.163	1.000															
(3) Instit. Investor Concen. (Per., Top 5)	-0.188	-0.148	1.000														
(4) Instit. Investor Concen. (Per., Other)	0.350	0.157	0.197	1.000													
(5) Media Attention	0.367	0.053	-0.092	0.065	1.000												
(6) Short Recommendation	0.024	-0.041	0.033	-0.023	0.054	1.000											
(7) Firm Size	0.514	0.287	-0.245	0.089	0.505	-0.041	1.000										
(8) Short Investment Horizon	-0.027	-0.044	-0.001	-0.054	0.037	0.278	-0.034	1.000									
(9) Location: Major City	-0.013	-0.022	0.014	0.013	-0.015	-0.003	-0.026	0.007	1.000								
(10) Location: Non-US	0.039	0.016	-0.029	-0.023	0.025	-0.018	0.059	-0.001	-0.454	1.000							
(11) Undergraduate Rank: Top	0.018	-0.020	0.001	0.015	0.005	-0.004	0.001	-0.035	0.164	-0.049	1.000						
(12) Undergraduate Rank: Bottom	-0.008	0.006	0.010	-0.009	-0.002	0.009	0.003	0.008	-0.076	-0.048	-0.201	1.000					
(13) Undergraduate Rank: Unranked	0.004	0.019	-0.013	-0.026	0.006	0.006	0.023	0.036	-0.197	0.157	-0.411	-0.212	1.000				
(14) Graduate Rank: Top	0.006	-0.020	0.012	0.013	-0.004	0.013	-0.015	0.006	0.180	-0.048	0.146	-0.052	-0.070	1.000			
(15) Graduate Rank: Bottom	0.005	0.031	-0.025	-0.009	0.003	-0.007	0.003	0.004	-0.037	0.004	-0.053	0.049	0.069	-0.076	1.000		
(16) Graduate Rank: Unranked	-0.004	0.011	-0.005	-0.015	-0.005	-0.002	-0.004	0.022	-0.048	0.057	-0.090	-0.020	0.083	-0.094	-0.019	1.000	
(17) Graduate Rank: No Grad.	-0.001	0.005	0.004	0.009	-0.006	-0.022	0.010	-0.032	-0.092	0.025	-0.044	-0.001	0.007	-0.768	-0.154	-0.192	1.000

Table 3: Logit Regression of Knowledge Sharing on Measures of Market Uncertainty

	M1		M2		M3		M4		M5	
Sell-Side Coverage[a]			4.267	***						
			(0.482)							
Firm Age[a]					0.701	***				
					(0.123)					
Media Attention[a]							0.710	***		
							(0.074)			
Instit. Investor Concen. (Per., Top 5)									0.952	***
									(0.167)	
Instit. Investor Concen. (Per., Other)									−1.122	***
									(0.142)	
Firm Size[a]	0.015	***	0.011	*	0.014	***	0.012	***	0.008	**
	(0.003)		(0.005)		(0.003)		(0.003)		(0.003)	
Short Investment Horizon	1.340	***	1.337	***	1.332	***	1.351	***	1.293	***
	(0.071)		(0.075)		(0.071)		(0.071)		(0.074)	
Location: Major City	0.017		0.042		0.010		0.017		0.066	
	(0.095)		(0.097)		(0.096)		(0.096)		(0.095)	
Location: Non-US	−0.462	**	−0.415	*	−0.465	**	−0.433	*	−0.429	*
	(0.179)		(0.172)		(0.177)		(0.178)		(0.179)	
Undergraduate Rank: Top	−0.202	*	−0.216	*	−0.205	*	−0.204	*	−0.198	*
	(0.083)		(0.085)		(0.083)		(0.083)		(0.084)	
Undergraduate Rank: Bottom	0.115		0.092		0.115		0.108		0.105	
	(0.143)		(0.135)		(0.141)		(0.143)		(0.136)	
Undergraduate Rank: Unranked	−0.091		−0.101		−0.095		−0.088		−0.104	
	(0.089)		(0.092)		(0.089)		(0.089)		(0.088)	
Graduate Rank: Top	−0.071		−0.082		−0.073		−0.076		−0.040	
	(0.138)		(0.133)		(0.137)		(0.138)		(0.131)	
Graduate Rank: Bottom	0.480	*	0.462	+	0.499	*	0.501	*	0.587	**
	(0.216)		(0.246)		(0.218)		(0.228)		(0.226)	
Graduate Rank: Unranked	0.326		0.238		0.342		0.308		0.271	
	(0.234)		(0.234)		(0.233)		(0.238)		(0.228)	
Graduate Rank: No Grad.	−0.186		−0.181		−0.182		−0.194		−0.158	
	(0.125)		(0.123)		(0.125)		(0.126)		(0.120)	
Constant	−2.153	***	−3.017	***	−2.268	***	−2.786	***	−2.179	***
	(0.440)		(0.587)		(0.438)		(0.444)		(0.453)	
Observations	19,093		17,362		19,093		19,093		16,889	
Log-likelihood	−8,498		−7,498		−8,477		−8,436		−7,453	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the investment professional-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

[a]The inverse of this measure was used in the regression.

Table 4: Logit Regression of Knowledge Sharing on Short Selling Recommendation

	M6		M7		M8	
Short Recommendation	0.524	***	0.595	***	0.522	***
	(0.083)		(0.085)		(0.085)	
Sell-Side Coverage[a]			4.457	***		
			(0.481)			
Instit. Investor Concen. (Per., Top 5)					0.920	***
					(0.167)	
Instit. Investor Concen. (Per., Other)					−1.105	***
					(0.143)	
Firm Size[a]	0.015	***	0.011	*	0.009	**
	(0.003)		(0.005)		(0.003)	
Short Investment Horizon	1.259	***	1.242	***	1.208	***
	(0.071)		(0.076)		(0.074)	
Location: Major City	0.022		0.049		0.070	
	(0.095)		(0.096)		(0.095)	
Location: Non-US	−0.445	*	−0.393	*	−0.409	*
	(0.179)		(0.172)		(0.179)	
Undergraduate Rank: Top	−0.205	*	−0.220	**	−0.202	*
	(0.083)		(0.085)		(0.084)	
Undergraduate Rank: Bottom	0.110		0.086		0.101	
	(0.141)		(0.133)		(0.135)	
Undergraduate Rank: Unranked	−0.092		−0.102		−0.104	
	(0.089)		(0.092)		(0.088)	
Graduate Rank: Top	−0.072		−0.080		−0.042	
	(0.135)		(0.131)		(0.130)	
Graduate Rank: Bottom	0.496	*	0.482	+	0.599	**
	(0.217)		(0.249)		(0.227)	
Graduate Rank: Unranked	0.338		0.257		0.284	
	(0.233)		(0.233)		(0.228)	
Graduate Rank: No Grad.	−0.184		−0.176		−0.157	
	(0.123)		(0.121)		(0.118)	
Constant	−2.176	***	−3.047	***	−2.190	***
	(0.439)		(0.582)		(0.453)	
Observations	19,093		17,362		16,889	
Log-likelihood	−8,465		−7,459		−7,424	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the investment professional-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
[a]The inverse of this measure was used in the regression.

Table 5: Logit Regression of Knowledge Sharing on Short Selling Recommendation (with Market Uncertainty Interactions)

	M9		M10		M11		M12	
Short Recommendation	0.546	***	0.651	***	0.320	*	0.218	
	(0.101)		(0.102)		(0.158)		(0.198)	
Firm Age[a]	0.693	***						
	(0.131)							
Sell-Side Coverage[a]			4.571	***				
			(0.493)					
Media Attention[a]					0.702	***		
					(0.077)			
Instit. Investor Concen. (Per., Top 5)							0.929	***
							(0.176)	
Instit. Investor Concen. (Per., Other)							−1.220	***
							(0.150)	
Short Reco. X Firm Age	−0.260							
	(0.324)							
Short Reco. X Sell-Side Coverage			−1.681					
			(1.592)					
Short Reco. X Media Attention					0.367	+		
					(0.188)			
Short Reco. X Instit. Inv. Concen. (Per., Top 5)							−0.238	
							(0.539)	
Short Reco. X Instit. Inv. Concen. (Per., Other)							0.978	*
							(0.392)	
Firm Size	0.015	***	0.011	*	0.012	***	0.009	**
	(0.003)		(0.005)		(0.003)		(0.003)	
Short Investment Horizon	1.255	***	1.243	***	1.259	***	1.209	***
	(0.072)		(0.075)		(0.072)		(0.074)	
Location: Major City	0.015		0.047		0.023		0.070	
	(0.095)		(0.096)		(0.096)		(0.094)	
Location: Non-US	−0.447	*	−0.397	*	−0.409	*	−0.413	*
	(0.178)		(0.172)		(0.178)		(0.179)	
Undergraduate Rank: Top	−0.208	*	−0.220	**	−0.211	*	−0.200	*
	(0.084)		(0.085)		(0.083)		(0.084)	
Undergraduate Rank: Bottom	0.110		0.087		0.102		0.103	
	(0.140)		(0.133)		(0.141)		(0.135)	
Undergraduate Rank: Unranked	−0.095		−0.101		−0.089		−0.101	
	(0.089)		(0.092)		(0.089)		(0.088)	
Graduate Rank: Top	−0.074		−0.079		−0.075		−0.044	
	(0.135)		(0.132)		(0.135)		(0.130)	
Graduate Rank: Bottom	0.514	*	0.486	*	0.520	*	0.605	**
	(0.218)		(0.248)		(0.230)		(0.226)	
Graduate Rank: Unranked	0.353		0.257		0.323		0.284	
	(0.232)		(0.234)		(0.237)		(0.229)	
Graduate Rank: No Grad.	−0.180		−0.175		−0.190		−0.157	
	(0.123)		(0.121)		(0.122)		(0.119)	
Constant	−2.289	***	−3.048	***	−2.813	***	−2.159	***
	(0.439)		(0.581)		(0.447)		(0.449)	
Observations	19,093		17,362		19,093		16,889	
Log-likelihood	−8,446		−7,459		−8,393		−7,420	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the investment professional-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

[a]The inverse of this measure was used in the regression.

Table 6: Logit Regression of Knowledge Sharing on Measures of Market Uncertainty (within-Investment Professional)

	R1		R2		R3		R4		R5	
Sell-Side Coverage[a]			1.982	**						
			(0.660)							
Firm Age[a]					0.333	*				
					(0.162)					
Instit. Investor Concen. (Per., Top 5)							0.721	**		
							(0.266)			
Instit. Investor Concen. (Per., Other)							−0.706	***		
							(0.192)			
Media Attention[a]									0.449	***
									(0.102)	
Firm Size[a]	0.013	***	0.015	**	0.013	***	0.008	*	0.011	***
	(0.003)		(0.005)		(0.003)		(0.004)		(0.003)	
Short Investment Horizon	1.430	***	1.399	***	1.429	***	1.385	***	1.431	***
	(0.077)		(0.083)		(0.077)		(0.082)		(0.077)	
Observations	6,395		5,671		6,395		5,657		6,395	
Log-likelihood	−2,763		−2,377		−2,760		−2,377		−2,753	

Notes: Sample restricted to only those investment professionals who utilized both justification types. Unit of analysis is the investment recommendation. Models contain investment professional, year, and industry fixed effects with standard errors in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
[a]The inverse of this measure was used in the regression.

Table 7: Logit Regression of Knowledge Sharing on Short Selling Recommendation (within-Investment Professional)

	R6		R7		R8	
Short Recommendation	0.382	***	0.416	***	0.343	**
	(0.102)		(0.107)		(0.106)	
Sell-Side Coverage[a]			2.124	**		
			(0.662)			
Instit. Investor Concen. (Per., Top 5)					0.715	**
					(0.266)	
Instit. Investor Concen. (Per., Other)					−0.711	***
					(0.193)	
Firm Size[a]	0.013	***	0.014	**	0.008	*
	(0.003)		(0.005)		(0.004)	
Short Investment Horizon	1.371	***	1.333	***	1.327	***
	(0.078)		(0.084)		(0.084)	
Observations	6,395		5,671		5,657	
Log-likelihood	−2,756		−2,369		−2,372	

Notes: Sample restricted to only those investment professionals who utilized both justification types. Unit of analysis is the investment recommendation. Models contain investment professional, year, and industry fixed effects with standard errors in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
[a]The inverse of this measure was used in the regression.

Chapter 2

From Audience to Evaluator: The Effect of Social Influence in Opt-in Evaluation Processes

2.1 Introduction

It is often difficult to gauge the quality of a candidate, good, or service (an offering) without experiencing it firsthand. Historically, professional critics have solved this information problem by providing ratings, rankings, and reviews for offerings across various domains (e.g., Ginsburgh 2003; Hsu 2006; Rao, Monin, and Durand 2005; Zhao and Zhou 2011). More recently, many firms address this issue by facilitating the rating process through a more democratized opt-in evaluation process (e.g., Glassdoor, TheFunded, TripAdvisor, and Yelp). These platforms offer any individual or firm who has experienced an offering the opportunity to opt in and rate its quality. Similar evaluation processes have also become integral to firm strategy, whereby firms allow their users or customers to rate the quality of their experiences with the products and services offered (e.g., Airbnb, TaskRabbit, Uber, and Upwork). Although the prevalence of the digital and sharing economy has increased the demand for and reliance on these ratings of quality (Dellarocas 2003; Dellarocas and Wood 2007; Sundararajan 2016), rating platforms for traditional offerings (e.g., books, childcare, doctors, employers) have also become commonplace.

The goal of these opt-in evaluation processes is straightforward: to triangulate on an unbiased and representative signal of quality that will be available to those considering that offering. The assumption is that democratizing the evaluation process will yield an independent and representative set of ratings of quality (Orlikowski and Scott 2013: 880). At first glance, this assumption seems plausible. For example, until a recent software update, Uber had not allowed its users to order a subsequent 'ride' without first rating the quality of their previous ride. In theory, a driver's current average rating represents the audience's opinion of quality up until that point, providing subsequent users with quality information. However, in general there is rarely any obligation to rate an offering, and anecdotal evidence suggests that only a small proportion of audience members opt to become evaluators. Therefore, while democratizing evaluation processes carries a promise of capturing independent and representative assessments of quality, there is also a risk that factors unrelated to an offering's quality could affect the evaluation process. Specifically, this shift to opt-in evaluation processes raises the following question: *What affects the likelihood that a rating for an offering occurs, and how does this selection affect the observed rating?*

Understanding these increasingly popular opt-in evaluation processes is especially critical given that the ratings they produce have direct economic impact on an offering. Specifically, social influence, stemming from exposure to the ratings of others, affects the likelihood that potential consumers decide to sample an offering (Hanson and Putler 1996; Salganik, Dodds, and Watts 2006; Salganik and Watts 2008; Senecal and Nantel 2004) and its success (e.g., Chevalier and Mayzlin 2006; Clemons, Gao, and Hitt 2006; Luca 2016; Melnik and Alm 2002). Furthermore, apart from their significant role in the digital and sharing economy, opt-in evaluation processes are also becoming more widely used within organizations. Their results have implications for individual careers (e.g., 360 review), entrepreneurship (e.g., Hallen and Pahnke 2016), and for firm strategy, as firms respond to the various ratings and rankings they are subject to (e.g., Chatterji and Toffel 2010, Espeland and Sauder 2007, Espeland and Stevens 1998).

In this paper, I posit that this social influence affects not only the likelihood that a person samples or consumes an offering, but also the likelihood that they rate it. Consistent with research that classifies ratings produced from opt-in evaluation processes as a form of public or collective good, I show that the presence of ratings from previous evaluators decreases the overall likelihood of subsequent ratings occurring, relative to when these ratings are not available. I then show that this social influence effect is heterogeneous with respect to the valence of an offering's available rating. Further, I disentangle two competing mechanisms—deviation and conformity—for explaining how exposure to ratings from others affects both the likelihood that a rating occurs and the type of subsequent ratings an offering receives.

A major challenge in addressing this research question is identifying the set of actors who are at risk of rating an offering in the first place, namely the audience from which evaluators emerge. We typically only observe those who have opted to become evaluators and the ratings they produce. For example, while a restaurant may serve thousands of patrons each month, only a handful may choose to subsequently rate their experience. I address this empirical challenge by leveraging unique data from the Real Investors Club (RIC, a pseudonym), an organization that provides an online knowledge-sharing platform for investment professionals in the investment management industry. The main purpose of this platform is to bring together buy-side (e.g., hedge fund, mutual fund) professionals to share investment strategies through investment recommendations (the offerings). However, investment professionals on RIC can also view and rate one another's recommendations. Using detailed data on investment-professional-level activity on RIC, I observe the entire evaluation process for each recommendation (offering): the investment professionals at risk of rating a recommendation, the subset of investment professionals who select to rate it, and the rating these evaluators give the recommendation. Further, to identify the causal impact of social influence on RIC's opt-in evaluation process, I leverage a natural experiment, related to whether an investment professional was exposed to the average rating from previous evaluators at the time they decided whether to rate a given recommendation. In this context, performance is also standardized and unbiased, which allows me to isolate how social influence affects the evaluation process despite the availability of a clear indicator of objective quality.

This research contributes to research on social influence, social valuation, and stratification, as well as evaluation processes more generally. I demonstrate how exposure to the ratings of others affects the likelihood that an evaluation occurs in the first place. Further, in line with stratification research on cumulative advantages (Merton 1948; Merton 1968) and disadvantages (DiPrete and Eirich 2006), I highlight how exposure to the ratings of others acts as a mechanism that helps sustain early leads, solidifying the chasm between the "haves and have nots." This research also provides a field-based test of social influence on the evaluation process beyond cultural markets, the usual context for these studies. In cultural markets, quality is especially difficult to discern, which could lead to a greater reliance on the ratings of others. More generally, this research has important implications for organizations. A reliance on ratings and rankings is becoming more common to organizational processes, affecting organizational strategy (Chatterji and Toffel 2010; Espeland and Stevens 1998; Espeland and Sauder 2007). Thus, this research informs how firms should think about the data-generating process of opt-in evaluation processes as well as their structure to increase the likelihood of collecting unbiased ratings of quality.

2.2 Opt-in Evaluation Processes

Evaluation processes can be broadly categorized into two types: *mandatory evaluations* and *opt-in evaluations*. In a mandatory evaluation an audience member is tasked with rating (or evaluating, ranking, reviewing) an offering (candidate, good, or service). For example, managers are commonly obligated to perform end-of-year evaluations of subordinates. Opt-in evaluations differ in that audience members choose whether to provide a rating for an offering. For example, at many universities, after taking a course, students can choose whether to rate its quality.

Traditionally, ratings of quality were entrusted to a specific set of individuals and firms, such as critics, experts, or judges (e.g., Benjamin and Podolny 1999; Bourdieu 1993; Caves 2000; Ginsburgh 2003; Greif 1993; Hsu 2006; Negro, Hannan, and Rao 2011; Rao, Monin, and Durand 2005; Zhao and Zhou 2011). Someone looking for a new restaurant to try might rely on the opinion of the local newspaper's food critic, or for a household vacuum might rely on the rankings supplied by *Consumer Reports*. In this model of evaluation, the set of evaluators is well defined and reasonably well known, and their evaluation methodology is most likely standardized and comparable. More recently, however, evaluation processes have evolved to offer non-experts the ability to "opt-in" and rate the quality of various offerings.

In particular, the digitization of markets has led to new, and much larger, platforms (e.g., Yelp, TheFunded, TripAdvisor) for disseminating these non-expert ratings of quality (see Dellarocas 2003 for a review). The introduction of these platforms has not only increased the availability of outlets for rating offerings but also democratized the evaluation process. Now, after experiencing[1] an offering, any person or firm can opt to rate the quality of their experience. Figure 1 illustrates the opt-in evaluation process on these rating platforms. Over time, more and more individuals or firms experience an offering; this cumulative set composes the audience for that offering, or the evaluator risk set—because any member of this audience has the opportunity to evaluate. Then, some audience members—the dark gray actors in the figure—opt to rate the offering, thereby becoming evaluators. As evaluators contribute ratings, the offering's average rating, which is available to those using the platform, adjusts accordingly. Unlike an expert's rating that is updated periodically, if at all, an offering's rating from an opt-in rating platform is a living organism.

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[1] In some cases, it is possible for an evaluator to not have experienced the offering that they are evaluating (see Anderson and Simester 2014 for an example). However, in the context under study, audience members can only evaluate an offering that they have experienced, which helps mitigate this issue.

[Figure 1]

The goal of democratizing the evaluation process, and allowing anyone the opportunity to rate, is to obtain an independent and more representative sample of ratings to provide to those potentially interested in that offering. In particular, the hope is that the average of these ratings triangulates on an unbiased and representative signal of quality for that offering. Firms that provide such rating platforms believe that this innovation to the evaluation process is helping to achieve this goal, as illustrated in the following quote from a TripAdvisor employee.

> When you compare user-generated content to...professional reviews, well, would you rather have comments from a hundred individuals about the quality of this hotel or from a single professional reviewer who works for a guidebook who stays at this hotel once every other year, who may or may not have his identity known or not, but just has the experience of one day?" (as quoted in *(Orlikowski and Scott 2013: 881)*

The main assumption is that the greater number of ratings collected, the better, as described by a TripAdvisor employee: "We want our results to be as authentic as we can possibly make them. In the end of the day, when you have 500 reviews it's almost hard for an algorithm to go wrong" (as quoted in (Orlikowski and Scott 2013: 880).

2.3 Social Influence and Opt-in Evaluation Processes

The effect of one actor's valuation, action, or belief on another actor's valuation, action, or belief, commonly referred to as social influence, is long documented in social science research (e.g., Asch 1951; Banerjee 1992; Coleman, Katz, and Menzel 1957; Hong, Kubik, and Solomon 2000; Merton 1957; Sherif 1936). For example, Asch (1951) showed that in an objective exercise with a clearly correct answer, a person became more likely to choose the wrong answer when they were purposely exposed to a majority opinion that supported this incorrect choice. Given the considerable amount of information asymmetry and uncertainty that exists regarding an offering's quality in most markets, it is not overly surprising that evaluation research has similarly documented a social influence effect. Specifically, this research has found that exposure to an offering's prior ratings affects the likelihood that potential consumers decide to subsequently sample it (e.g., Chevalier and Mayzlin 2006; Clemons, Gao, and Hitt 2006; Luca 2016; Melnik and Alm 2002). Namely, these quality ratings, from past evaluators, help clarify the ambiguity surrounding an offering's quality for these potential consumers and thus facilitate their decision.

For example, Luca (2016) found that the average rating displayed on Yelp causally affects restaurant revenue; a half-star increase leads to a corresponding 2.5 to 4.5 percent change in a restaurant's revenue, *ceteris paribus*. Similarly, through an experimental design, Salganik and colleagues (2006; 2008) showed that the number of downloads a song by a previously unknown band receives increases the incidence of subsequent downloads. Therefore, regardless of whether the ratings produced from these democratized opt-in evaluation processes triangulate on quality, those considering an offering treat them as credible signals of quality.

Evaluation research on this social influence effect, namely how exposure to the ratings of others affects the evaluation process, has primarily focused on the attention stage of the evaluation process. During this stage actors are deciding whether to sample an offering: to patronize a given restaurant or to hire a given freelancer. However, these evaluation processes are fluid. Actors are simultaneously deciding whether to sample an offering while others are deciding whether to rate that same offering. Moreover, ratings from previous evaluators are available to both sets of actors; thus social influence may be affecting not only the attention an offering receives, but also the rating process. Specifically, I posit that exposure to the ratings of previous evaluators affects the likelihood that subsequent ratings occur. If this is true, it casts doubt on the ability of democratized opt-in evaluation processes to provide independent and representative ratings of quality.

2.3.1 Rating Availability: Likelihood That a Rating Occurs

By design, democratized opt-in evaluation processes rely on people who have experienced an offering opting to rate it; thus there is no obligation to rate the quality of an offering. Consistent with this fact, anecdotal evidence suggests that ratings in these systems are produced by only a small subset of the audience who could have opted to evaluate. For example, Highland Kitchen, a restaurant located near Cambridge, Massachusetts, serves about 2,000 customers per week.[2] All diners are in the audience and therefore at risk of evaluating the restaurant on one (or more) of the many platforms available (e.g., TripAdvisor, Yelp). However, on Yelp, the most prominent restaurant rating platform in the United States, only about 1,000 ratings have occurred since the restaurant opened in 2007. This small proportion is not unique to the restaurant industry, or to the consumer domain more generally. For example, the highest-rated question on Stack Overflow, a knowledge-sharing platform for developers, has received approximately 819,000 views but only 15,095 ratings in the four years that the question has been active.[3]

This under-provision of ratings is also consistent with research that has classified ratings from democratized opt-in evaluation processes as a form of public or collective good (Avery, Resnick, and Zeckhauser 1999; Bolton, Katok, and Ockenfels 2004). These ratings have been categorized as such because the average rating from previous evaluators is often made available to all considering that offering, without any prerequisite that they themselves contribute

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2 This estimate was obtained by the author from the restaurant.

3 http://stackoverflow.com/questions/11227809/why-is-it-faster-to-process-a-sorted-array-than-an-unsorted-array. The rating displayed on Stack Overflow to the audience is the difference between up votes and down votes; this number is the absolute sum of either vote type and was obtained by the author from the firm.

a rating. For example, restaurant-goers can browse Yelp's rating platform without submitting a rating or even having an account. Moreover, most rating platforms provide some form of anonymity, allowing actors to use the rating system without consequence. Similarly, students at many universities can access a course's previous ratings (i.e., course/subject evaluations) without having contributed a rating in the past or committing to contribute a future rating.

When we consider the availability of ratings as a collective good, it is not entirely surprising that only a small subset of audience members opt to provide ratings. The likelihood that any given audience member opts to evaluate an offering is expected to be low—as seen in the anecdotal examples involving Highland Kitchen and Stack Overflow. Further, we should also expect that the likelihood that a rating occurs decreases once audience members have access to the ratings from previous evaluators, since providing one's own rating makes a more marginal contribution when quality information is already available from prior evaluators. Thus, I posit a negative social influence effect on the likelihood that subsequent ratings occur:

Hypothesis 1: *The likelihood that a rating occurs for an offering will decrease when an average prior rating for that offering is available to audience members, relative to when this rating is not available.*

2.3.2 Rating Valence: Deviation or Conformity?

When a rating is available to audience members, its level or valence relays important information about the offering's quality—signaling that the offering is of low, middle, or high quality. Commonly, an offering's rating is displayed as an average of the individual ratings from each previous evaluator. If you were to visit the Yelp page for Highland Kitchen, you would see that 1,059 ratings have occurred and that their average is roughly 4 stars (out of 5).[4] This allows potential audience members of this restaurant to analyze its rating in an

[4] https://www.yelp.com/biz/highland-kitchen-somerville.

absolute sense—4 out of 5 stars seems like a high rating—as well as relative to other similar offerings, here, restaurants. Therefore, the effect of social influence on the likelihood that subsequent ratings occur may be heterogeneous with respect to the valence of the available rating. Specifically, the social influence effect stemming from exposure to prior ratings may not uniformly decrease the likelihood that subsequent ratings occur. I adjudicate between two competing mechanisms—deviation and conformity—where a desire to deviate from the prevailing opinion or a desire to conform to it may affect the likelihood that a rating occurs.

Both mechanisms assume that the main purpose of opting to rate an offering is to express one's opinion about its quality. Although there is often no obligation to opt into rating an offering, as discussed above, it should be the case that at certain times sharing one's rating of quality is considered more valuable. In the case of deviation, the audience member chooses to rate because they have an experience that *differs* from the average rating from previous evaluators to date. For example, if a firm selects a freelancer because of his high average rating, but has a low-quality experience with him, they may be motivated to rate their experience in order to lower that rating, which will help caution future firms considering this candidate. Similarly, if an individual patronizes a coffee shop and has a great experience, but sees that others have given the coffee shop low ratings, they may be motivated to share their high-quality experience to increase the coffee shop's average rating. Implicit in this line of reasoning is that if these actors had an experience in line with the offering's prevailing rating they would be less motivated, relatively speaking, to share this opinion.

If selection is occurring because potential evaluators do not see their opinions reflected in the offering's current rating, we should see evidence of this in the ratings they leave for that offering. Specifically, if deviation is motivating selection, offerings that begin with a high (low) average rating will receive more subsequent low (high) ratings. This will lead to a quality signal composed of a more diverse set of ratings; however, it may not be representative of the average audience member's opinion of quality.

Alternatively, a conformity mechanism is one by which audience members are motivated to further reward (penalize) offerings that have garnered an average rating that signals high (low) quality by providing consistent positive (negative) ratings. This idea of a "self-fulfilling prophecy" is a cornerstone of sociological inquiry (Merton 1948; Merton 1968), and it is often invoked to explain the rigidity observed in status hierarchies and the perpetuation of inequality more generally (e.g., Podolny 1993; Simcoe and Waguespack 2011). The logic is this: when past assessments of quality are available to current evaluators, subsequent similar assessments of quality are likely to occur, leading to *conformity*.

Research in social psychology has demonstrated that conformity occurs because individuals and firms are susceptible to changing their own opinion after they are exposed to the opinions of others (Asch 1951). Similarly, in evaluation research, Muchnik and colleagues (2013) found evidence consistent with conformity in the up- and down-voting behavior of the comments left on articles on a social news-aggregation website. Through a field experiment, where they randomly assigned up and down votes to comments, they find that while all comments are on average likely to receive subsequent up votes, those whose first vote was an up-vote receive the greatest advantage due to subsequent conformity.

If democratized opt-in evaluation processes are to achieve their goal of triangulating on a representative and unbiased signal of quality, it is necessary to question whether conformity is the mechanism driving subsequent evaluators to rate. If winners and losers receive a larger share of attention from evaluators, this may reinforce the ratings from previous evaluators, leading to a cumulative advantage (Merton 1948; Merton 1968) or cumulative disadvantage (DiPrete and Eirich 2006) respectively. Specifically, exposure to the average rating of previous evaluators may be a mechanism by which early leads and setbacks are sustained, creating a self-fulfilling prophecy.

For both mechanisms, exposure to an average rating from previous evaluators that signals particularly low or high quality, relative to middle quality, affects the likelihood that subsequent ratings occur. Thus, I posit a heterogeneous effect of social influence on the likelihood that subsequent ratings occur:

Hypothesis 2: *The likelihood that subsequent ratings occur for offerings with an available rating is higher for offerings with an average rating that signals low or high quality, relative to middle quality.*

2.4 Scope Conditions

The above arguments may be limited to anonymous evaluation processes. Many opt-in evaluation processes, such as the context for this study, provide anonymity to audience members and evaluators. Anonymity is commonly achieved via some combination of veiling the behaviors of audience members and hiding their identity. Some platforms veil the behaviors of audience members, meaning that others cannot identify the set of offerings each audience member chose to experience, whether they opted to rate those offerings, or the ratings they gave. Other platforms achieve anonymity by not disclosing information about individual actors or by allowing users to disguise their identity with pseudonyms. In either case, anonymity allows evaluators to deviate or to conform, or even to engage in some combination of conformity and deviation, without consequence. For example, an evaluator may conform publicly—stating that they find an offering to be of high quality—but penalize the offering privately—giving it a low rating. Although all types of democratized opt-in evaluation processes have significant economic impact, it is necessary to make this distinction, as we may expect different predictions for evaluation processes that do not offer any form of anonymity.

2.5 Empirical Context

The context for this study is the Real Investors Club (RIC, a pseudonym) an organization that provides an online knowledge-sharing platform for buy-side (e.g., hedge fund, mutual fund) investment professionals from around the world. These professionals analyze and buy (and sell) securities (e.g., common stock) as part of their day-to-day work using their investors' capital, as opposed to sell-side analysts, whose primary job function is to disseminate their recommendations of a security to a client base. RIC is a private platform; therefore, buy-side investment professionals must apply for access to RIC. The knowledge shared concerns market opportunities in the form of investment recommendations (recommendations) to buy (or to short-sell) a security. Recommendations include a position (e.g., buy or sell); a price target, the price a recommender expects the stock to reach; and an investment horizon, the approximate time for this price to be reached (e.g., one year).

Recommendations also include a detailed justification that presents the analysis that supports the position being recommended, which is monitored by RIC to ensure that a minimum level of quality is met. Detailed justifications (Figure 2) must be at least 600 words (averaging over 1,400 words) and must typically include an in-depth analysis of macroeconomic trends, the firm/stock's[5] industry, the firm (e.g., financial reports, management meetings, projections), and a discussion of how the valuation (i.e., the price target) was reached.[6] Once a recommendation is submitted, it joins the list of all previously submitted recommendations on RIC and is available to all active RIC members. Recommendations are listed in reverse

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[5] A stock represents ownership in a firm; therefore, I use both terms interchangeably.

[6] Recommenders are also given an option to submit a simple justification instead of a detailed justification. Simple justifications can be no longer than 40 words (avg. 24) and include little to no analysis. For a broader discussion of the differences between justification types, please see Botelho (2016). Recommendations are separated by justification type, and only those recommendations that include a detailed justification undergo the evaluation process; therefore, the sample for my analyses is limited to the subset of recommendations that included a detailed justification.

chronological order and include basic information: the stock being recommended, the position (e.g., long vs. short), the name and employer name of the recommender, and the performance of the recommendation to date. To access a recommendation's detailed justification, one must "click on" it.

[Figure 2]

In addition to submitting recommendations, investment professionals on RIC can evaluate, or rate, the recommendations of others at any time. The rating process on RIC is multistage and is opt-in. An investment professional joins the audience for a recommendation by clicking on it, and she becomes an evaluator by opting to provide a rating for that recommendation (Figure 3). This process is akin to most opt-in evaluation processes; for example, after reading a book (entering the audience set) an actor has the opportunity to subsequently rate that book (entering the evaluator set). Recommendations and their justifications are the offering being rated in this context. These recommendations can be rated on a scale from 1 to 5, in integer increments, along two dimensions: quality of the analysis (justification rating) and expected performance of the position (return rating); free-form comments can also be left. The justification rating is intended to measure whether the evaluator believes that the detailed justification for the recommendation was of high quality, namely that it included a relevant and rigorous analysis that convincingly supported the recommendation. One RIC member described the justification rating to me as the "good analyst rating." The return rating measures the evaluator's belief that the rate of return from the recommendation will be achieved.

I distinguish between two types of evaluation—giving attention and giving a rating, the latter of which is what is most commonly thought of as an evaluation—by calling those who have chosen to give attention "audience members" and those who have given a rating "evaluators." In this context, the entire evaluation process is anonymous. Although investment professionals are identified when they submit a recommendation, RIC veils their viewing and rating behaviors from other investment professionals on the platform. This anonymity allows investment professionals to behave freely without concern for how their actions will be seen by others. Further, anonymity is important given that the evaluation process on RIC is bilateral—investment professionals can simultaneously act as producers (by recommending a stock) and consumers (by viewing and evaluating the recommendations of others)—and thus we may be concerned that evaluation behavior is driven by reciprocity or retaliation (e.g., Diekmann et al. 2014).

[Figure 3]

2.6 Identifying Evaluator Risk Set and Social Influence Natural Experiment

A major empirical challenge in answering the question under study is the ability to identify the evaluator risk set, namely the audience members who have an opportunity to evaluate. Although evaluation research has underlined the importance of capturing this risk set, it is typically difficult to do so since we often observe only those evaluations that occur. A similar empirical issue occurs in a hiring context, where it is difficult to analyze the factors that affect the hiring process without observing every individual who applied for a job, namely the candidate pool (see Fernandez and Weinberg 1997 for a discussion). To form a more complete understanding of the data-generating process for opt-in evaluation processes, we need to capture each individual who experienced an offering and could have rated it. For example, the audience for a book would be every reader of that book. Next, it is necessary to identify who from that audience emerges as an evaluator. To address this challenge, I collected unique data from RIC. Specifically, I tracked individual investment professionals' viewing and rating histories, for approximately 8 months. Therefore, for each recommendation in this timeframe, I identified which investment professionals clicked on a given recommendation—the audience—and then who from this audience opted to rate that recommendation—the evaluators.

A second empirical challenge relates to identifying the effect of social influence, which in this case stems from exposure to a recommendation's average rating to date. Generally, it is very difficult to use observational rating data to causally identify a social influence effect. An offering's average rating to date is available to would-be audience members and evaluators as soon as the initial rating occurs. However, in my context, I leverage a natural experiment to address this challenge, which allows me to causally identify the effect of social influence on this evaluation process. Until a recommendation receives four total ratings, in any combination of justification and return ratings, the cumulative average rating to date is unavailable to audience members. Once the fourth total rating is received, the average rating to date becomes available to all subsequent audience members. Most evaluators rate along both dimensions; thus, typically after the second evaluator opts to rate a recommendation the average rating for the recommendation becomes available. Moreover, audience members see only the average rating to date, and not the distribution of ratings. Of the 534 recommendations, 320 recommendations receive at least four total ratings, and these recommendations do not differ along any observation variable relative to recommendations that receive less than four total ratings.

2.7 Data

I collected data from RIC on the investment professionals using this platform, the recommendations submitted, and the details of the evaluations of each of these recommendations from 2008 to 2013. Although the data were used to construct measures that are included in my analyses, the focal data are from an 8-month subsample (in 2013), where I was able to track individual-level data pertaining to who viewed what recommendations and when a rating occurred. These data from RIC were supplemented with data from external databases: financial market data came from the Center for Research in Security Prices (CRSP), and industry data came from Compustat.

Analysis was limited to recommendations for common stock in the CRSP database. CRSP covers the major U.S. exchanges (e.g., NASDAQ and NYSE); therefore, it does not include data on stocks that trade via the over-the-counter Bulletin Board. The sample used in this study includes 534 recommendations by 419 recommenders. In total, these recommendations received 30,957 unique viewing events from 1,339 unique audience members, which generated 1,445 justification ratings from 286 unique evaluators.

2.7.1 Ratings

The first set of analyses focuses on how social influence, measured as exposure to the ratings from previous evaluators, affects the likelihood that ratings for a recommendation occur. The outcome variable *Rating Occurred* takes a value of 1 if an audience member rates a recommendation, conditional on viewing (i.e., being an audience member) it, and it takes a value of 0 if an audience member did not rate the recommendation. The next set of analyses unpacks how this social influence also affects the level of the rating that an offering receives. For these analyses, the outcome variable *Justification Rating Difference,*[7] was calculated as the difference between an evaluator's rating and the recommendation's average rating at the time of evaluation. It is bounded between −4, when an evaluator gives a 1 star rating to a recommendation with an average of 5 stars, and +4, when an evaluator gives a 5 star rating to a recommendation with an average of 1 star.

[7] To avoid redundancy, I excluded analyses of the return rating as an outcome variable. Approximately 90 percent of evaluators rate recommendations along both dimensions, with a very high within-evaluator correlation between both rating types (0.81). I chose to present results from the justification rating because if an evaluator only rated a recommendation along one dimension they were three times more likely to leave a justification rating and the return rating was only recently added.

2.7.2 Social Influence

Three independent variables were used in the main analyses. Social influence is operationalized as the availability of an average rating from previous evaluators, at the time an audience member clicks on a recommendation, which occurs after a recommendation has received four total ratings. The variable *Available Rating* takes a value of 1 if the average rating to date is available to the audience member, and 0 otherwise. The valence of this social influence is measured using two dichotomous variables. *Top Average Justification Rating* takes a value of 1 if the available average justification rating is greater than or equal to 4 stars, and 0 if the available average justification rating is less than 4 stars. *Bottom Average Justification Rating* takes a value of 1 if the available average justification rating is less than or equal to 2 stars, and 0 if the available average justification rating is greater than 2 stars. The reference group, *Middle Average Justification Rating,* will be recommendations with an average justification rating between 2 and 4 stars.

2.7.3 Control Variables

It is possible that characteristics of the recommendation or the recommender influence the likelihood that a rating occurs, as well as the rating the recommendation receives. To account for this, I control for recommendation- and recommender-level variables. At the recommendation level, models include controls for performance, expected return, recommendation type, investment horizon, investment type, and firm size. At the recommender level, models control for a recommender's gender, education, experience on the platform, and relationship with the audience member.

The variable *Recommendation Performance* measures the difference between the recommendation's rate of return and the S&P 500's rate of return, during the time between the recommendation being submitted and the focal audience member viewing the recommendation. Rate return (R_t) is calculated as $R_t = \frac{(p_t - p_{t-1}) + d_t}{p_{t-1}}$, where p_t is the security's price at time period t, the most recent close price when the audience member is viewing the recommendation; p_{t-1} is the most recent close price of the security at the time the recommendation was submitted; and d_t accounts for the sum of any distributions (e.g., dividends) between $t-1$ and t. The ability to control for a standardized and unbiased measure of quality is a key feature of this setting. If any two investment professionals invest in the same security—at the same time—they will realize identical returns, regardless of any external factors. *Expected Return* is operationalized as $(\frac{price\ target - price\ at\ recommendation}{price\ at\ recommendation})$ and captures the recommender's expected profit from following this recommendation, at the time it was submitted.

Certain recommendation types may also influence the evaluation process. For example, information on short-selling positions is often difficult to acquire; therefore, recommendations that focus on short positions may be of interest to the audience, and such recommendations may be rewarded in terms of evaluation. Short-selling is the practice of selling borrowed shares of a stock with the guarantee of repurchasing and returning these shares to the lender—along with any distributions, such as a dividend—later. *Short Position* takes a value of 1 if the focal recommendation type is to short-sell a stock, and a value of 0 for buy (or long) positions. Similarly, a recommendation's investment horizon is controlled for through the variable *Short Investment Horizon,* which takes a value of 1 when the recommendation has an investment horizon of less than 1 year, and 0 if the investment horizon was greater than 1 year. Additionally, the *Investment Type* of the recommendation is self-reported by the recommender in one of four categories: value (the reference category), event (e.g., regulatory change), growth, and other. The variable *Firm Size (B)* represents the market capitalization of the stock (price $\times$ shares outstanding). Finally, the recommendation's industry is controlled for using industry-level fixed effects. I use the 24 two-digit NAICS sectors and an indicator for a missing NAICS sector.

Given evidence that gender factors into evaluations (e.g., Botelho and Abraham 2017; Foschi 1996; Ridgeway and Correll 2004; Ridgeway and Smith-Lovin 1999), I also control for the likely gender of a recommender using the IBM InfoSphere Global Name Management Tool. This algorithm scores first names from 0 to 99 for how likely a given name is associated with the female gender (Maguire 2012). This process is used because self-reported gender is not required on RIC and it matches the data-generating process. Audience members are not presented with a recommender's gender when viewing recommendations, but they do see their first name. For over 80 percent of my sample, I collected data on which universities they attended for undergraduate and graduate school. I then matched each undergraduate school with the 2013 U.S. News College Ranking (U.S. News and World Report 2013b) and each graduate school with either the 2013 U.S. News MBA Ranking (U.S. News and World Report 2013a) or the 2013 Financial Times Global MBA Ranking (Financial Times 2013) for non-U.S. business schools. The measure *Audience Elite Education* takes a value of 1 if an investment professional attended a school ranked in the top 20 for either undergraduate or graduate school. I also control for the number of past recommendations that a recommender has made, in case more-experienced recommenders are evaluated differently (*Recommendation Count*).

Investment professionals on RIC are given a direct medium for communication, through a messaging system on the platform. A threat to any rating system is the potential for "gaming" the evaluation process, which occurs when evaluators are driven by ulterior motives unrelated to experiencing the offering, such as reciprocity and reciprocation and is often difficult to account for. Although the anonymity of this evaluation processes mitigates these concerns, it could be the case that investment professionals ask one another for favorable ratings. I mitigate this issue by accounting for the communication between any two investment professionals on RIC. The variable *Recommender and Audience Communicated* takes a value of 1 if the recommender and audience member exchanged a message before the audience member viewed the recommendation, and 0 otherwise. While I do not have access to the content of these messages, the assumption is that those who are connected on the platform are more likely to be frequent and favorable evaluators of one another than those who are not connected.

Table 1 provides summary statistics for each of the variables discussed above. The first descriptive statistic of interest is that only about 5 percent of the views (or clicks) that a recommendation receives lead to a rating occurring. Although the value of the number differs from the above anecdotal examples, it provides concrete empirical evidence that ratings are rare events. This baseline level also suggests support for the notion of ratings being a collective good. Additionally, and consistent with previous research on evaluations, the ratings on RIC are mostly positive: 54 percent of the total justification ratings are either 4 or 5 stars, and the average justification rating is 3.42 stars. This is similar to data provided by Yelp (2016), which shows that 67 percent of the ratings on its platform are 4s or 5s.

In line with the fact that the industry under study is selective, half the audience members (as well as recommenders) attended an elite institution for either undergraduate or graduate school. Communication between an audience member and a recommender is rare: less than 3 percent of viewing events (and 5 percent of rating events) occur between an audience member and a recommender who have previously communicated. This provides evidence that RIC members are not outwardly gaming the evaluation process by soliciting ratings for their recommendations. Table 2 is a correlation table for these variables.

[Table 1]

[Table 2]

2.8 Results

2.8.1 Likelihood That a Rating Occurs

To understand how social influence affects the likelihood that a rating occurs for a recommendation, I examine how the availability of an average rating from previous evaluators affects this likelihood. Consistent with hypothesis 1 (Table 3, Model 1A and Model 1B), I find that once a recommendation's average rating becomes available, the likelihood that subsequent ratings occur decreases substantially. Specifically, the odds that a recommendation receives a rating are about 1.44 times lower when the average rating from previous evaluators is available (Model 1B; $p < 0.001$) relative to when the average rating is not available.

Although leveraging the natural experiment on RIC helps rule out most endogeneity concerns, this effect may be driven by unobserved recommendation-level or investment-professional-level heterogeneity. To explore this possibility, Model 1C introduces recommendation fixed effects and Model 1D introduces investment-professional (audience-member) fixed effects (Table 3). The analysis in Model 1C compares the likelihood that a rating occurs for the same recommendation depending on whether its average rating is available to audience members, ignoring recommendations that fail to reach four total ratings during my study period. The results are robust to this specification: looking within the same recommendation, when an average rating is available to investment professionals, the odds that a subsequent rating occurs are about 3.71 times lower than when that recommendation's rating was not available (Model 1C; $p < 0.001$). Model 1D compares the likelihood that the same investment professional opts to rate recommendations depending on whether they are exposed to a recommendation's average rating or not; the results are also robust to this specification.

[Table 3]

Although these results provide strong evidence that the availability of an average rating decreases the likelihood that subsequent ratings occur for a recommendation, it is plausible that this effect may be temporal. In particular, this pattern could be caused by the fact that later ratings are always less likely to occur than earlier ones, resulting in a general downward trend. Thus, it may be that choosing one point in time and analyzing the likelihood that a rating occurs before versus after it merely reflects this negative slope. While this possibility does not invalidate the argument leading to hypothesis 1, that the existence of a quality signal for an offering decreases the demand for subsequent audience members to opt to rate, it must be addressed to develop a more complete understanding of this social influence effect. Figure 4 plots the effect of number of ratings on the likelihood that a rating occurs for a recommendation, examining recommendations that receive at least four total ratings during the study period. Before a recommendation's rating becomes available, the likelihood that a rating occurs is approximately 10 percent. However, once the recommendation's rating becomes available, the likelihood that a rating occurs significantly decreases, to about 4 percent.

[Figure 4]

Importantly, this shows that the above results do not simply capture a downward trend; instead, the availability of an average rating from previous evaluators leads to a discontinuous jump in the likelihood that a rating occurs. This provides conclusive and causal evidence for hypothesis 1, identifying that social influence affects the likelihood that a rating occurs. Specifically, the likelihood that a rating occurs for an offering decreases significantly when an average rating for that offering becomes available, relative to when this average rating is not available. Additionally, these results provide some of the first field-based evidence that ratings closely resemble a collective good (Avery, Resnick, and Zeckhauser 1999; Bolton, Katok, and Ockenfels 2004).

The logic leading to hypothesis 2 argues that a rating's valence, from previous evaluators, is also important to consider when predicting the likelihood that a rating occurs. From Model 2A (Table 4), recommendations that have an average rating that signals high quality (4 stars or higher) have higher odds of receiving subsequent ratings than recommendations with an average rating that signals middle quality. There is no such effect for recommendations with a bottom average rating (2 stars or lower). This may lead to the conclusion that for high-quality recommendations the social influence effect, of a rating being available, is mitigated. However, with this information alone, it remains unclear whether investment professionals on RIC share a similar rubric of quality and are likely to all rate these recommendations, or whether exposure to the ratings of others is driving this effect.

To adjudicate between these possible explanations, I introduce an interaction of top (bottom) justification rating and the availability of the average rating (*Available Rating* $\times$ *Top Average Justification Rating* and *Available Rating* $\times$ *Bottom Average Justification Rating*) in Model 2B (Table 4). Consistent with hypothesis 2, the effect of social influence on the likelihood that a rating occurs is differs depending on whether the average rating signals low or high quality. In other words, when the available average rating signifies that a recommendation is of particularly high or low quality, a rating is more likely to occur than if the available average rating signals middle quality. Furthermore, this result highlights that the positive effect of *Top Average Justification Rating* in Model 2A is driven by social influence stemming from exposure to prior ratings, as indicated by the positive and significant coefficient on the related interaction term. This analysis also helps unpack the null effect of a bottom average justification rating seen in Model 2A (Table 4). The presence of a bottom average justification rating leads to a marginally lower likelihood of a rating occurring when that rating is unavailable ($p = 0.066$)—suggesting that audience members may have a similar rubric of what constitutes low quality—but it leads to a higher likelihood of a rating occurring when the recommendation's rating is available. This provides causal evidence that the social influence effect on the likelihood that a rating occurs is heterogeneous with respect to the valence of the available rating.

[Table 4]

A logit regression was used because the main dependent variable, *Rating Occurred,* is a binary variable. An issue with this approach is interpreting the interaction effect, which is not necessarily solved by using a linear probability model specification, making calculating the marginal effects important (Ai and Norton 2003). Thus, Figure 5 presents a margins plot of the effect of rating valence on the likelihood that subsequent ratings occur, examining recommendations that receive at least four total ratings during the study period. This graph is also helpful because while I split a recommendation's average justification rating into three buckets for ease of presentation in Table 4, this plot can intuitively show the effect of rating availability on a continuous measure of average justification rating. Figure 5 confirms the results from Table 4.

[Figure 5]

These results provide strong support for hypothesis 2, that social influence has heterogeneous effects on the likelihood that subsequent ratings occur. Specifically, social influence stemming from available prior ratings reduces the likelihood of subsequent ratings only for offerings that have received ratings signaling middle quality. For offerings starting with either a low or high average rating, exposure to prior ratings decreases the likelihood of subsequent ratings occurring, however, this likelihood is higher than when the prior rating signals middle quality. This heterogeneous effect of social influence has implications for the number of ratings an offering receives, which will affect the perceived strength of the quality signal for those recommendations. Specifically, the quality signal for recommendations that have received low or high ratings will seem stronger relative to recommendations that have received a middle average rating, since it comprises a greater number of ratings. It is next important to understand how this selection affects the observed rating of a recommendation, namely if selection is due to evaluators deviating from or conforming to the average rating they are exposed to.

2.8.2 Deviation or Conformity?

In the next set of analyses, I use ordinary least squares regressions to predict *Justification Rating Difference,* which is the difference between an evaluator's rating and the recommendation's average rating at the time of evaluation. A deviation close to 0 means that the focal rating is close to the average rating the recommendation has received, whereas a deviation closer to $-4/+4$ represents a large deviation from the average rating a recommendation has previously received. Therefore, the absolute value of the coefficient demonstrates the strength of the deviation, and the sign of the coefficient demonstrates the direction (lower or higher).

Model 3A (Table 5) analyzes the main effect of a recommendation's average rating valence on the subsequent ratings it receives, irrespective of the rating available to the audience. Here, recommendations with a *Top Average Justification Rating,* on average, receive subsequent ratings that are almost a full star lower ($p < 0.001$). Conversely, recommendations with a *Bottom Average Justification Rating,* on average, receive subsequent ratings that are almost 0.75 stars higher. Model 3B (Table 5) begins to disentangle the competing predictions that audience members are motivated to rate recommendations whose available average rating signals low or high quality to deviate from or to conform to that rating.

The coefficients on the interaction *Available Rating* $\times$ *Top Average Justification Rating* and *Available Rating* $\times$ *Bottom Average Justification Rating* highlight that the ratings that occur after the average rating from previous evaluators becomes available are driven by conformity and *not* deviation. Specifically, as the coefficients on *Top Average Justification* and *Bottom Average Justification* show (Model 3B, Table 5), before evaluators are exposed to a recommendation's average rating, there is a strong deviation. However, when evaluators are exposed to a recommendation's average rating, they are more likely to conform to this average rating. In particular, evaluators presented with a low and high average rating are more likely to produce a similar rating than those presented with a middle average rating. Figure 6 plots this effect using a continuous variable of average rating for those recommendations that receive at least four total ratings during the study period. This figure shows that once a recommendation's average rating becomes available, subsequent evaluators submit a rating much closer to the average they are exposed to—close to 0 rating difference.

[Table 5]

[Figure 6]

Therefore, initially top-rated recommendations benefit from a cumulative advantage, whereas initially bottom-rated recommendations suffer from a cumulative disadvantage. This is especially surprising because I do not find any evidence that recommendations with an initial bottom rating underperform those with an initial top rating.

2.8.3 Effect of Available Rating on Subsequent Attention

The main contribution of this research is to highlight how social influence affects the likelihood that a rating occurs and the subsequent ratings an offering receives. However, there is also an opportunity to examine how the level of the rating that a recommendation receives affects the likelihood that potential audience members click on the recommendation, giving it attention. Specifically, investment professionals can screen investment recommendations based on the (coarse) average rating it has received to date; those recommendations that have not received four total ratings, however, are automatically excluded from this filter. To understand the implications of the level of ratings on subsequent attention, I analyzed how the ratings received in a recommendation's first week affect the subsequent attention it received through the end of the study period. I find that recommendations with a *Top Average Justification Rating* (4 stars or higher) receive nearly 62 percent more attention, or are clicked on significantly more, than recommendations with a lower average justification rating in subsequent weeks, but only if this rating is available (Table 6). This result is consistent with prior research identifying that social influence stemming from the availability of ratings affects the likelihood that potential consumers decide to experience the offering, or become audience members (e.g., Chevalier and Mayzlin 2006; Luca 2016). Moreover, this result has key economic consequences when we consider the main reason that investment professionals come to platforms such as RIC: to attract attention to their investment opportunities. Therefore, these early ratings play a significant role in the amount of attention a recommendation will end up receiving.

[Table 6]

2.9 Discussion

Democratizing the opt-in evaluation processes has allowed any individual or firm who has experienced an offering (candidate, good, or service) the opportunity to rate its quality. The purpose of 'opening up' the evaluation process is to collect independent ratings of quality in an effort to triangulate on a representative and unbiased signal of quality for an offering. However, anecdotal evidence suggests that only a small proportion of audience members opt to become evaluators in the first place. Therefore, while democratizing evaluation processes carries a promise of capturing independent and representative assessments of quality, there is also a risk that factors unrelated to an offering's quality could motivate selection into evaluation. The next important step in this line of inquiry is to understand the extent to which the goals of these processes are realized. Specifically, we need to elucidate the conditions under which ratings are more likely to occur and the factors that affect the types of ratings an offering receives. Progress on this question is critical because these evaluation processes are integral to the sharing economy and increasingly prevalent across a number of organizational processes.

There are two important empirical challenges in understanding how social influence affects the likelihood that ratings occur, which I overcome in this study. First, we are typically unable to observe the risk set of potential evaluators, namely the audience who has experienced an offering. Second, opt-in evaluation processes are frequently structured in a way that does not allow careful examination of social influence effects on subsequent ratings. Specifically, once an offering receives its first rating, that quality signal is commonly available to all those considering sampling and rating that offering (e.g., Amazon, Healthgrades, TripAdvisor, Yelp). To address these challenges, I leverage unique data from an online knowledge-sharing platform that allow me to identify the entire set of actors at risk of rating and the subset that opt to become evaluators. Moreover, I leverage a natural experiment to causally identify the effect of social influence on the likelihood that a rating occurs and the level of a rating that is given.

I find that exposure to an offering's average rating, from previous evaluators, decreases the likelihood that subsequent ratings for that offering occur, on average. However, this effect is not constant; the effect of social influence stemming from prior ratings varies based on the valence of the average prior rating. The effect of social influence is limited to those offerings with an average rating that signals middle quality, such that subsequent ratings are significantly less likely once the average rating is available. In the case of offerings with prior ratings that signal low or high quality, the likelihood that these recommendation receive subsequent ratings is greater than recommendations with prior ratings that signal middle quality. Furthermore, my findings reveal that a desire to conform is the mechanism driving evaluators to over-select in these cases. This results in recommendations that initially receive low and high ratings subsequently receiving a greater number of ratings that are consistent with this early average.

These findings contribute to research on social influence, social valuation, stratification, and evaluation processes more broadly. Most research on the effect of social influence on opt-in evaluation processes focuses on how exposure to an offering's ratings affects the amount of attention it receives (e.g., Chevalier and Mayzlin 2006; Clemons, Gao, and Hitt 2006; Luca

2016; Melnik and Alm 2002; Salganik, Dodds, and Watts 2006; Senecal and Nantel 2004). This study complements existing research by demonstrating that this social influence effect is broader, affecting other aspects of evaluation processes. The mere availability of ratings to audience members considering whether to produce a rating also limits the extent to which the ratings produced are independent.

Thus, an offering's available average rating is simultaneously responsible for motivating audience members to opt to rate its quality and for the rating these evaluators give. This leads to a self-fulfilling prophecy whereby subsequent ratings resemble those to which evaluators are exposed. Therefore, the availability of ratings from previous evaluators is a mechanism that helps sustain an offering's early lead or setback, leading to a cumulative advantage or disadvantage (DiPrete and Eirich 2006; Merton 1948; Merton 1968), and hinders the probability that an offering's observed rating is representative of the larger audience. This conformity also means that offerings that start with low or high average ratings of quality will receive more ratings, which has important implications for the perceived strength of the associated quality signal. As a rating is substantiated by more ratings, the quality signal for the offering is thought to become less noisy (Luca 2016). These findings illustrate that because of their starting condition, these offerings will emit a particularly strong high- or low-quality signal. Thus, while we may consider democratized opt-in evaluation processes as a way to even the playing field and to reduce the likelihood of inequality in the evaluation of quality, their current structure may instead widen the chasm between "the haves and have nots."

Furthermore, most field-based evaluation research has focused on offerings in cultural markets. The setting under study offers an opportunity to examine an opt-in evaluation process in a professional setting. This extension is essential given the growing popularity of evaluation processes across a number of contexts with direct implications for firms and individuals. For example, Instacart, a grocery delivery service, allows consumers to rate the quality of their experience with the shopper who selected and delivered their groceries. A negative rating will lead to fewer and smaller orders given to the shopper, affecting their overall compensation (Erbentraut 2015). Similar evaluation processes are also being incorporated within larger, more bureaucratic firms. For example, GE is in the process of abandoning its decades-old end-of-year employee-evaluation process conducted by a manager in favor of an ongoing dialogue, where "suggestions can come from anyone in an employee's network" (Baldassarre and Finken 2015). More generally, there is much to be learned about the various structures these evaluation processes can take and the mechanisms that will affect evaluative outcomes.

Also important is that these findings come from one context, and that features of the specific evaluation process under study may contribute to my findings. Unlike with unilateral opt-in evaluation processes, investment professionals in this context can simultaneously act as producers and evaluators. Although the RIC platform's anonymity helps mitigate concerns around reciprocity and retaliation in bilateral evaluations, these findings may not generalize to unilateral opt-in evaluation processes where producers and evaluators are separate (e.g., BeerAdvocate, Goodreads, Yelp). However, this structure most closely resembles the type of opt-in evaluation process present within an organization (e.g., 360 review) and within an industry (e.g., the context under study). Therefore, what this study lacks in its ability to generalize to unilateral opt-in evaluation processes, it gains in being able to speak to evaluation processes within a firm or industry. Further, given that this is a professional context, where these investment professionals are motivated to identify quality, the presence of a social influence effect is surprising. This suggests that a similar social influence effect should be found more broadly—if similar data can be collected for a unilateral opt-in evaluation processes—an opportunity for future research.

It may also be the case that the anonymity offered by RIC, namely that a member's viewing and rating behavior is withheld from the community, leads investment professionals to rate differently than they would if their identity were known. Although different forms of anonymity are frequent in opt-in evaluation processes, an interesting avenue for future research would be to disentangle the effect of social influence when anonymity is removed. It may be that concerns related to reciprocity, reputation, or status could mitigate or magnify the found social influence effect. Similarly, the rating in this setting is only displayed as the average, with distributional information withheld from the audience. Hence, the availability of more detailed information regarding the average rating may mitigate or exacerbate the found social influence effect. For example, Leung and Wang (2016) find that the number of movie ratings increases when there is contention in the individual ratings for a movie.

Another promising avenue for future research is to understand the impact of the ratings generated by opt-in evaluation processes on firms beyond affecting the attention and subsequent ratings they receive. For example, after Uber faced allegations of sexual harassment, its app's rating plunged. Whereas its lifetime rating was 3.7 stars (out of 5), from the end of January 2017 to February 21, 2017, the app received almost 4,000 1-star ratings(Bell 2017), and many reviews noted the sexual harassment allegations. Future research can help elucidate how coordinated efforts to reduce an offering's rating compare to more traditional types of protest. Analyzing firm response would also be worthwhile. Unlike a protest that may end, the impact of thousands of low ratings may be harder to repair.

This study also has important practical implications for organizations and managers relying on these opt-in evaluation processes or considering implementing them. A significant focus of those considering the structure of opt-in evaluation processes is addressing the presence of fake or incentivized ratings (e.g., Anderson and Simester 2014; Perez 2016). These occur when evaluators are motivated to positively or negatively rate an offering, regardless of their experience of the offering or their true opinion of its quality. Many firms have attempted to eliminate these types of ratings, or at least to control for their existence, by only including in that offering's average rating those ratings from evaluators who they can verify experienced the offering. Although this is a necessary step, it does not address the fact that these evaluators may be influenced by ratings from previous evaluators.

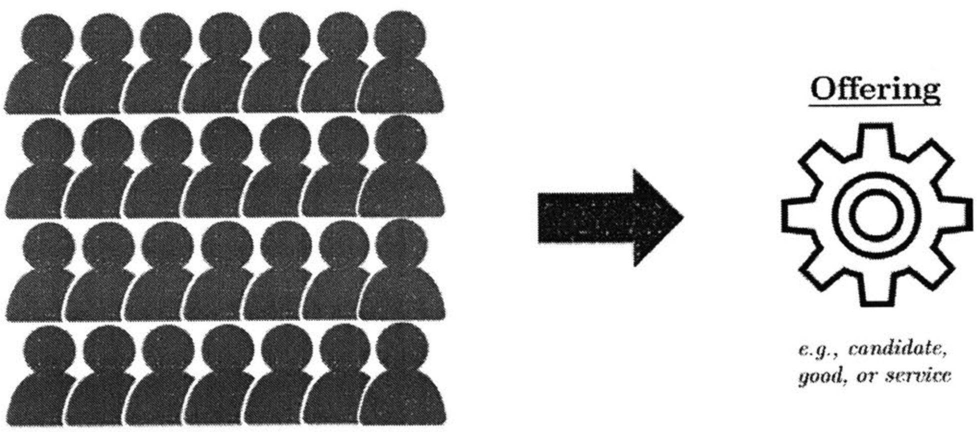
These findings present a dilemma for firms utilizing opt-in evaluation processes in this regard. Given the impossibility of supplying ratings to those considering an offering but not to those who have opted to rate it, it is unclear what can be done to improve the likelihood of collecting independent ratings of quality. I propose that these firms should implement a significant "quiet period," one that allows for the collection of independent ratings but that also supplies this information to the audience after the quiet period ends. For example, the first 40 ratings for an offering would be collected without the average rating to date being available. Then, after these 40 ratings were collected, the average rating would be freely available. Although this structure does not prevent evaluators, after the initial 40, from conforming to the average rating, it at least provides a substantive quality signal at the start. Firms should then "reset" the availability of an offering's rating and then reinstitute a quiet period in order to update this quality signal in future periods. This is important because for some offerings a long history of ratings is not necessarily valuable, especially if subsequent evaluators are conforming. For example, of what value is a ten-year average rating for a restaurant? Instead, consumers want is a short-term signal, which this model helps achieve. While quiet periods do not exclude bias, for example the independence of the initial ratings must be confirmed; however, it is a simple and cost-effective change that firms can easily experiment with.

Overall, organizations must decide how more democratized evaluation processes fit with their larger organizational goals. For example, the ability of employees to give feedback to one another may be very productive in terms of providing complete information. However, it also risks stifling innovation, which benefits from heterogeneous viewpoints and productive discourse and discussion. If employees feel that they could be penalized by their colleagues after a disagreement, they may become more reserved. Also, firms must thoughtfully consider strategy changes in response to being rated (Chatterji and Toffel 2010; Espeland and Sauder 2007; Martins 2005). Given the social influence effect of ratings on key outcomes, this is a sensible strategy. However, if ratings, as I show, are similarly susceptible to social influence, organizations should take pause about their willingness to update. On one hand, if ratings continue to affect attention, then even following a suboptimal strategy may create value. On the other hand, if ratings change or the cost of pivoting is prohibitive, it may erode value in the long term.

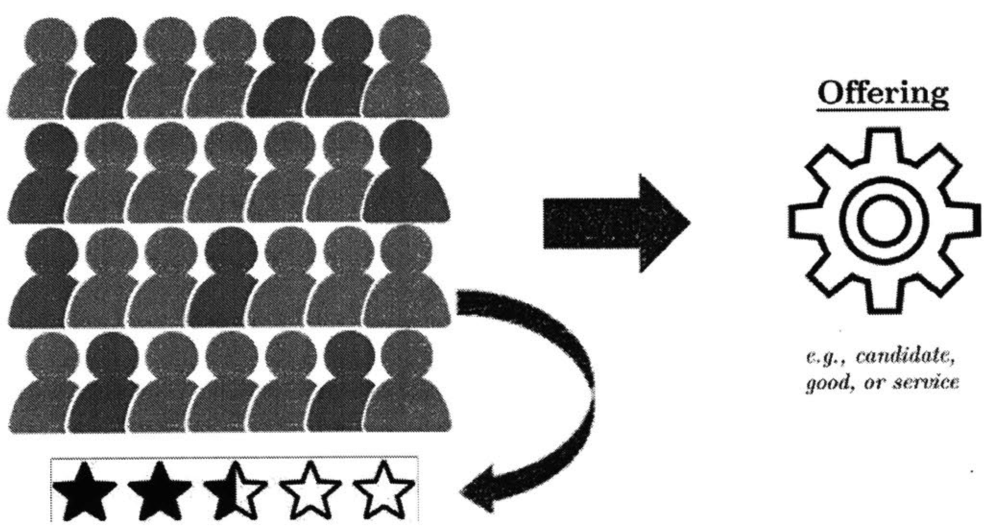
2.10 Figures and Tables

Figure 1: Steps of the Opt-in Evaluation Process

Step 1: Audience Members Experience an Offering

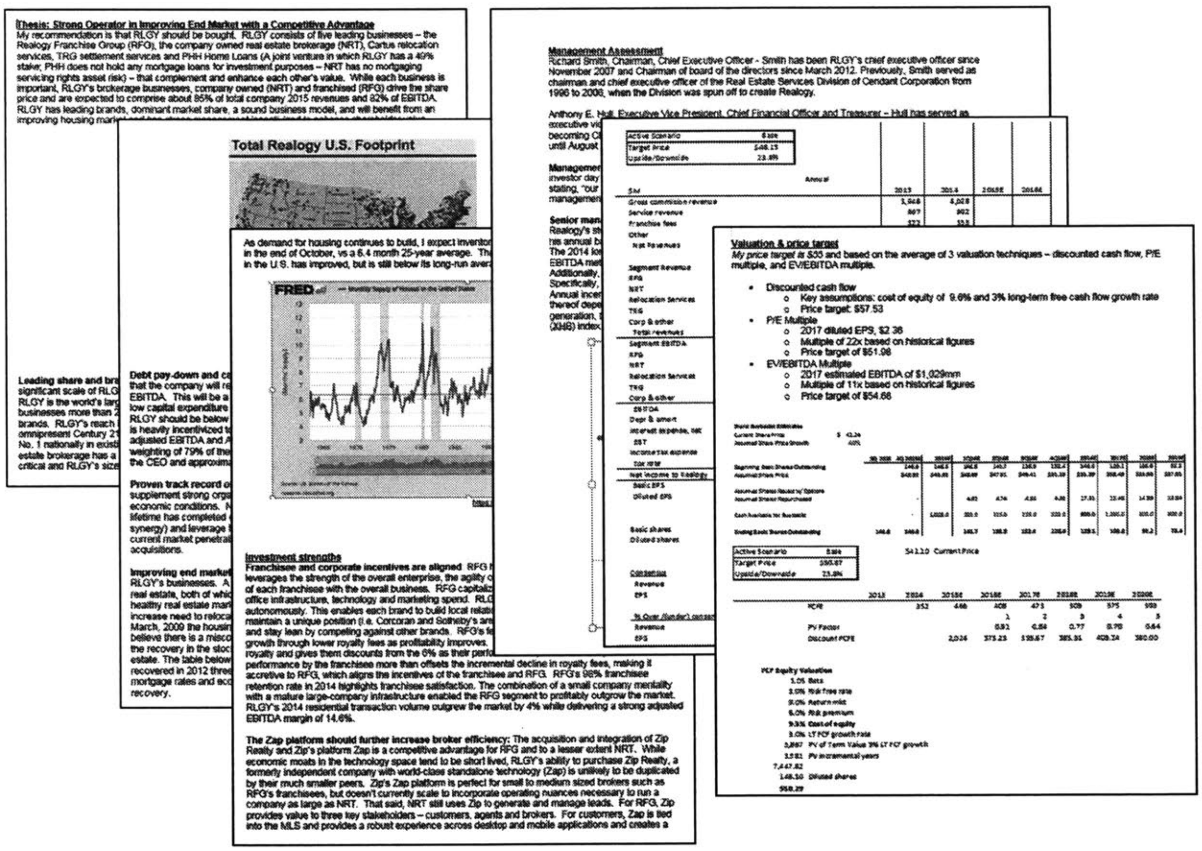


Step 2: Some Audience Members Evaluate the Offering and Produce a Rating



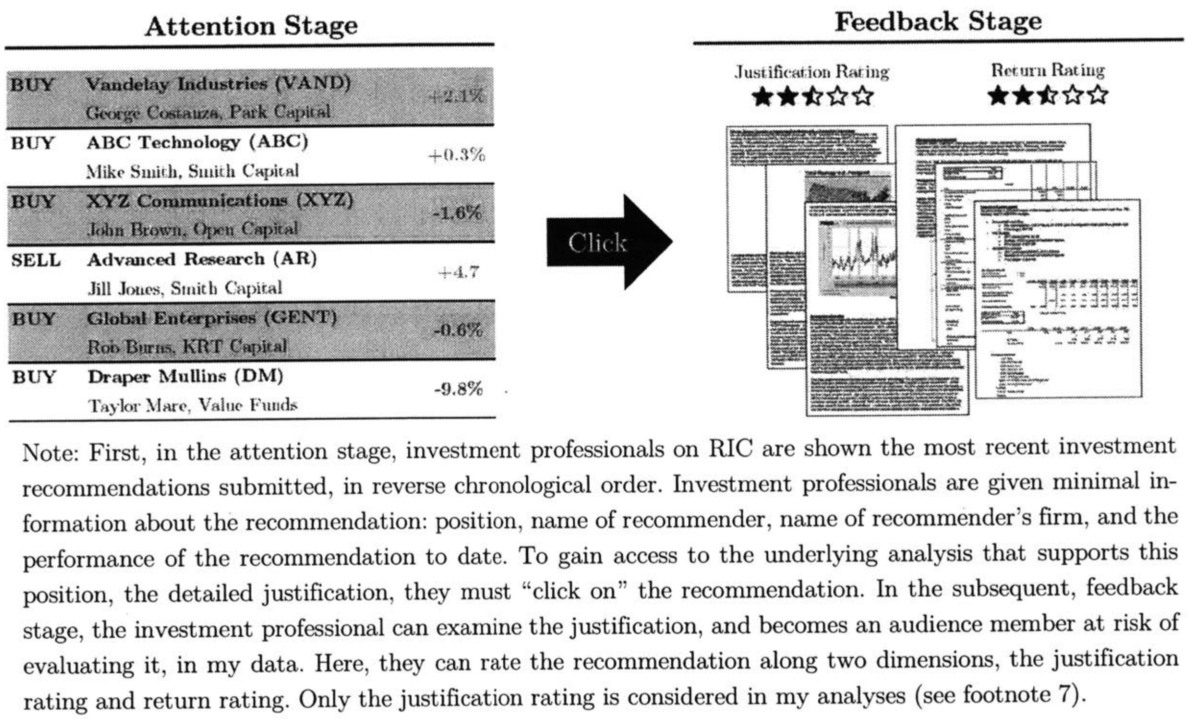
Note: In the first step, over time, audience members experience an offering. At any given point, the total set of these individuals or firms to date is considered the risk set for that offering. In the second step, after experiencing an offering, some audience members opt to evaluate it (represented by the dark gray figures), and the average of those individual ratings is the average rating for that offering.

Figure 2: Example of a Detailed Justification



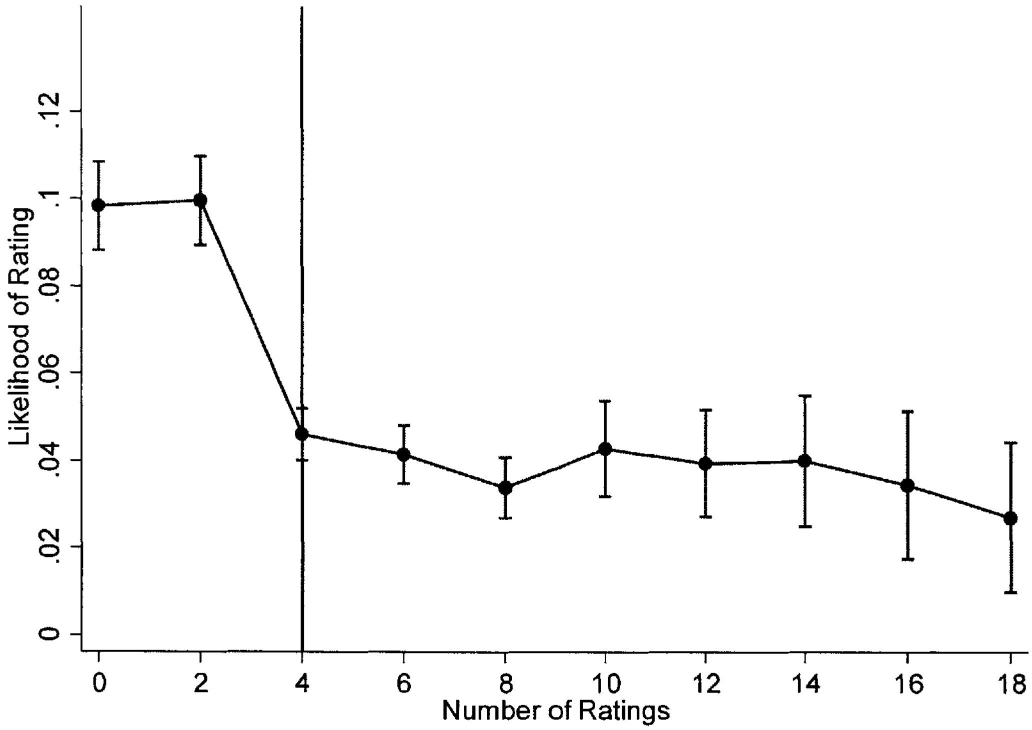
Note: This is representative example of the type of information and analysis that is included in a detailed justification on RIC. However, this example was obtained by the author, from a buy-side investment professional, and is not from the RIC database. Further, this analysis is meant to serve as an example and is not a recommendation of the stock discussed.

Figure 3: RIC's Multistage Evaluation Process



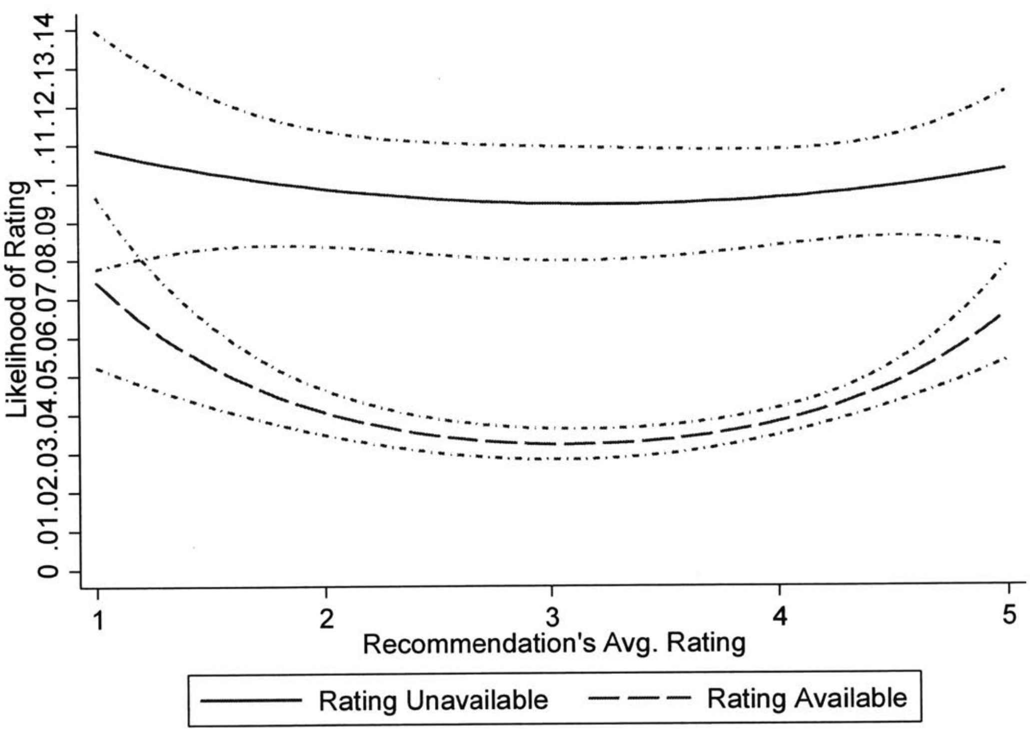
Note: First, in the attention stage, investment professionals on RIC are shown the most recent investment recommendations submitted, in reverse chronological order. Investment professionals are given minimal information about the recommendation: position, name of recommender, name of recommender's firm, and the performance of the recommendation to date. To gain access to the underlying analysis that supports this position, the detailed justification, they must "click on" the recommendation. In the subsequent, feedback stage, the investment professional can examine the justification, and becomes an audience member at risk of evaluating it, in my data. Here, they can rate the recommendation along two dimensions, the justification rating and return rating. Only the justification rating is considered in my analyses (see footnote 7).

Figure 4: Effect of Rating Availability on Audience Members Opting to Rate



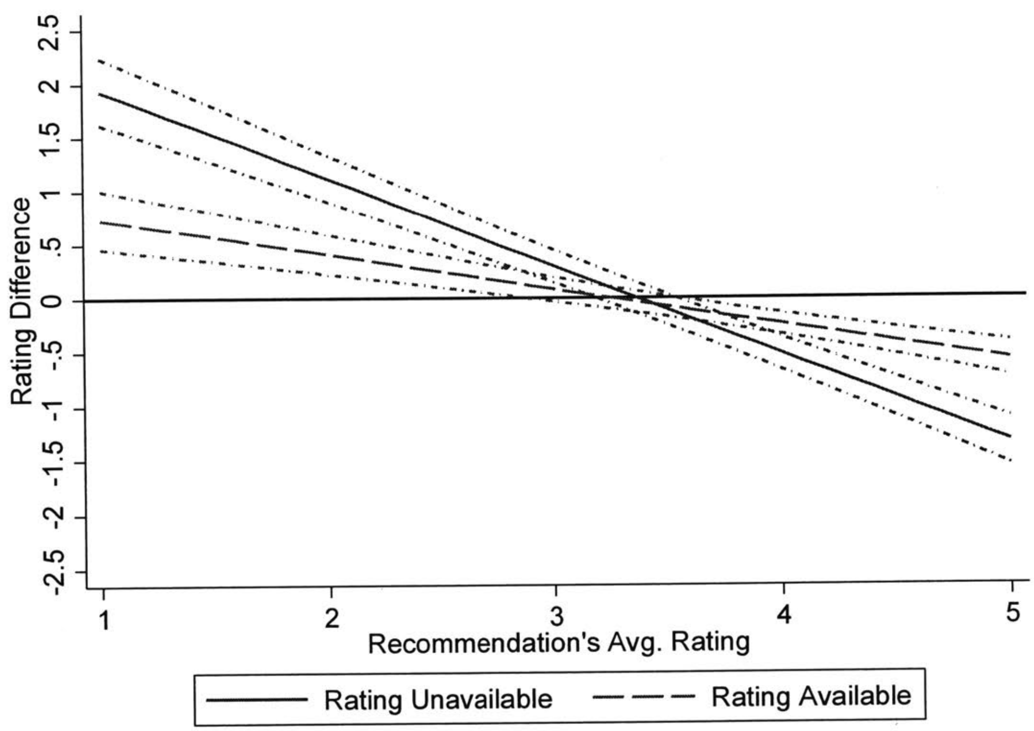
Note: This figure plots the likelihood that a recommendation receives a justification rating based on the number of previous ratings the recommendation has received. Previous ratings become available to the audience member after the fourth rating has occurred (represented by black vertical line). Confidence intervals (95%) are represented by gray bars. Over 90 percent of evaluators rate along both justification quality and return ratings; therefore, the number of ratings is usually even. For recommendations that received a justification rating from an evaluator, and not a return rating, I subtracted 1 from its number of ratings (e.g., a recommendation with 3 ratings will be grouped with those with 2). Results are robust to excluding this adjustment. Further, less than 2 percent of recommendations receive more than 18 ratings, therefore, the graph was restricted to this number. This sample is restricted to recommendations that receive at least four total rating during the period under study.

Figure 5: Effect of Rating Valence on Audience Members Opting to Rate



Note: This figure plots the likelihood that a recommendation receives a justification rating based on a continuous measure of the recommendation's average justification rating, at the time the audience member clicked on the recommendation. This sample is restricted to recommendations that receive at least four total rating during the period under study.

Figure 6: Effect of Rating Valence on Rating Difference



Note: This figure plots the likelihood that a recommendation receives a justification rating based on a continuous measure of the recommendation's average justification rating, at the time the audience member clicked on the recommendation. This sample is restricted to recommendations that receive at least four total rating during the period under study.

Table 1: Summary Statistics of Key Variables

	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
Rating Occurred	30,957	0.048	0.214	0.000	1.000
Rating Difference[a]	995	-0.066	1.413	-4.000	4.000
Independent Variables					
Available Rating	30,957	0.509	0.500	0.000	1.000
Top Avg. Justification Rating[b]	22,451	0.454	0.498	0.000	1.000
Bot. Avg. Justification Rating[b]	22,451	0.174	0.379	0.000	1.000
Aud. Elite Education	30,957	0.507	0.500	0.000	1.000
Control Variables					
Recommendation Performance	30,957	0.008	0.106	-0.822	1.579
Expected Return	30,957	0.920	3.271	0.001	60.491
Short Position	30,957	0.201	0.401	0.000	1.000
Short Investment Horizon	30,957	0.432	0.495	0.000	1.000
Investment Type: Event	30,957	0.222	0.416	0.000	1.000
Investment Type: Growth	30,957	0.191	0.393	0.000	1.000
Investment Type: Other	30,957	0.137	0.344	0.000	1.000
Firm Size (B)	30,957	6.358	20.820	0.014	219.53
Female Name Score	30,957	5.787	18.694	0.000	99.000
Reco. Elite Education	30,957	0.518	0.500	0.000	1.000
Reco. Count	30,957	4.806	5.939	1.000	42.000
Reco. and Aud. Communicated	30,957	0.026	0.158	0.000	1.000

[a]Conditional on a justification rating occuring.
[b]Conditional on at least one justification rating having occurred.

Table 2: Correlation of Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Available Rating	1.000															
(2) Top Avg. Justification Rating	-0.021	1.000														
(3) Bot. Avg. Justification Rating	-0.251	-0.418	1.000													
(4) Aud. Elite Education	-0.017	0.012	0.002	1.000												
(5) Recommendation Performance	0.005	-0.008	0.002	-0.014	1.000											
(6) Expected Return	0.044	-0.030	-0.051	-0.000	0.007	1.000										
(7) Short Position	0.090	0.157	-0.077	0.021	-0.033	0.022	1.000									
(8) Short Investment Horizon	0.009	-0.126	0.059	0.006	0.026	-0.064	0.146	1.000								
(9) Investment Type: Event	0.038	-0.028	-0.077	0.002	0.047	-0.002	-0.009	0.286	1.000							
(10) Investment Type: Growth	-0.061	-0.156	0.138	0.006	0.014	-0.043	-0.107	-0.080	-0.260	1.000						
(11) Investment Type: Other	0.056	0.116	-0.051	0.006	-0.030	0.013	0.614	0.090	-0.213	-0.194	1.000					
(12) Firm Size (B)	0.002	-0.071	0.082	-0.005	-0.028	-0.037	-0.082	-0.099	-0.072	0.088	-0.057	1.000				
(13) Female Name Score	-0.063	0.001	0.007	0.007	-0.025	-0.020	0.040	0.063	0.038	-0.039	0.011	0.025	1.000			
(14) Reco. Elite Education	0.019	0.071	-0.069	0.010	0.007	0.061	0.145	-0.025	-0.045	0.025	-0.004	-0.096	0.069	1.000		
(15) Reco. Count	0.096	0.065	-0.121	0.003	-0.003	0.242	0.088	0.039	0.132	-0.006	-0.057	0.008	-0.049	0.126	1.000	
(16) Reco. and Eval. Communicated	-0.005	0.025	-0.034	0.029	0.004	0.073	0.009	-0.004	0.033	-0.017	-0.020	-0.017	-0.020	0.030	0.163	1.000

Notes: Correlations greater than or equal to $|0.0126|$ are significant at $p \leq 0.05$.

Table 3: Logit Regressions of Audience Member Opting to Rate Recommendation on Rating Availability

	Model 1A		Model 1B		Model 1C		Model 1D	
Available Rating	-0.347	***	-0.365	***	-1.310	***	-0.132	*
	(0.087)		(0.085)		(0.066)		(0.064)	
Recommendation Performance	-0.591	**	-0.587	**	-0.204		-0.598	+
	(0.197)		(0.196)		(0.400)		(0.342)	
Expected Return	0.008		-0.000				-0.000	
	(0.007)		(0.008)				(0.009)	
Short Position	0.133		0.107				0.145	
	(0.097)		(0.097)				(0.101)	
Short Investment Horizon	-0.041		-0.031				-0.018	
	(0.065)		(0.064)				(0.067)	
Investment Type: Event	0.017		-0.002				-0.028	
	(0.068)		(0.067)				(0.088)	
Investment Type: Growth	-0.058		-0.074				-0.117	
	(0.083)		(0.085)				(0.087)	
Investment Type: Other	0.078		0.113				0.050	
	(0.101)		(0.102)				(0.119)	
Firm Size (B)	0.002		0.002	+			0.001	
	(0.001)		(0.001)				(0.001)	
Female Name Score			-0.003	*			-0.004	*
			(0.001)				(0.002)	
Reco. Elite Education			-0.009				0.028	
			(0.066)				(0.064)	
Reco. Count			0.010	*			0.010	+
			(0.005)				(0.005)	
Reco. and Eval. Communicated			0.721	**			-0.338	*
			(0.268)				(0.151)	
Constant	-3.039	***	-3.104	***				
	(0.463)		(0.462)					
Industry FE	Y		Y		Y		Y	
Recommendation FE	N		N		Y		N	
Audience FE	N		N		N		Y	
Observations	30,957		30,957		22,848		16,294	
Log-likelihood	-5,917		-5,896		-4,273		-3,541	

Notes: Unit of analysis is the viewing event. Models without recommendation/audience fixed effects have robust standard errors, clustered at the audience-member-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 4: Logit Regressions of Audience Member Opting to Rate Recommendation on Rating Availability and Valence

	Model 2A		Model 2B	
Available Rating	-0.353	***	-0.642	***
	(0.083)		(0.138)	
Top Avg. Justification Rating	0.232	**	-0.006	
	(0.081)		(0.136)	
Bot. Avg. Justification Rating	0.057		-0.290	+
	(0.103)		(0.158)	
Available Rating X Top Avg. Just. Rating			0.309	*
			(0.151)	
Available Rating X Bot. Avg. Just. Rating			0.597	**
			(0.201)	
Recommendation Performance	-0.711	***	-0.720	***
	(0.215)		(0.214)	
Expected Return	0.008		0.009	
	(0.009)		(0.009)	
Short Position	0.047		0.054	
	(0.108)		(0.106)	
Short Investment Horizon	0.023		0.016	
	(0.073)		(0.073)	
Investment Type: Event	-0.042		-0.032	
	(0.084)		(0.085)	
Investment Type: Growth	-0.051		-0.058	
	(0.083)		(0.083)	
Investment Type: Other	0.131		0.124	
	(0.123)		(0.123)	
Firm Size (B)	0.003	*	0.003	*
	(0.001)		(0.001)	
Female Name Score	-0.005	**	-0.005	**
	(0.002)		(0.002)	
Reco. Elite Education	0.071		0.069	
	(0.079)		(0.078)	
Reco. and Eval. Communicated	0.774	**	0.775	**
	(0.273)		(0.270)	
Constant	-3.219	***	-3.099	***
	(0.612)		(0.612)	
Observations	22,417		22,417	
Log-likelihood	-4,113		-4,109	

Notes: Sample excludes observations before the first rating occurred in order to have a comparison. Unit of analysis is the viewing event. Models contain industry fixed effects with robust standard errors, clustered at the audience-member-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 5: OLS Regressions of Rating Difference on Rating Availability and Valence

	Model 3A		Model 3B	
Available Rating	-0.041		-0.320	*
	(0.093)		(0.153)	
Top Avg. Justification Rating	-0.840	***	-1.392	***
	(0.104)		(0.166)	
Bot. Avg. Justification Rating	0.728	***	0.996	***
	(0.147)		(0.224)	
Available Rating X Top Avg. Just. Rating			0.871	***
			(0.180)	
Available Rating X Bot. Avg. Just. Rating			-0.834	***
			(0.238)	
Recommendation Performance	0.856		0.669	
	(0.762)		(0.776)	
Expected Return	0.006		0.006	
	(0.020)		(0.018)	
Short Position	0.171		0.088	
	(0.136)		(0.139)	
Short Investment Horizon	-0.043		0.002	
	(0.082)		(0.079)	
Investment Type: Event	0.098		0.080	
	(0.119)		(0.121)	
Investment Type: Growth	-0.186		-0.124	
	(0.113)		(0.111)	
Investment Type: Other	0.015		0.008	
	(0.166)		(0.163)	
Firm Size (B)	0.001		0.002	
	(0.002)		(0.002)	
Female Name Score	-0.001		-0.001	
	(0.003)		(0.003)	
Reco. Elite Education	0.118		0.120	
	(0.102)		(0.105)	
Reco. Count	-0.004		-0.008	
	(0.006)		(0.006)	
Reco. and Eval. Communicated	0.785	***	0.776	***
	(0.182)		(0.173)	
Constant	1.087	***	1.260	***
	(0.264)		(0.356)	
Observations	995		995	
R-Square Adj.	0.160		0.208	

Notes: Sample excludes observations before the first rating occurred in order to have a comparison. Unit of analysis is the rating. Models contain industry fixed effects with robust standard errors, clustered at the audience-member-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 6: Negative Binomial Regression of Post First Week Attention on Rating Availability and Valence

	Model 4A		Model 4B	
Available Rating	0.491	***	0.355	***
	(0.069)		(0.091)	
Top Avg. Justification Rating (First Week)	0.115		-0.184	
	(0.080)		(0.123)	
Bot. Avg. Justification Rating (First Week)	-0.269	**	-0.295	*
	(0.092)		(0.124)	
Avail. Rating X Top Avg. Just. Rating (First Week)			0.481	**
			(0.158)	
Avail. Rating X Bot. Avg. Just. Rating (First Week)			0.057	
			(0.181)	
Expected Return	0.015		0.016	
	(0.014)		(0.014)	
Short Position	0.198	+	0.179	
	(0.115)		(0.114)	
Short Investment Horizon	0.007		0.019	
	(0.070)		(0.069)	
Investment Type: Event	0.128		0.162	+
	(0.095)		(0.095)	
Investment Type: Growth	-0.250	**	-0.249	**
	(0.089)		(0.089)	
Investment Type: Other	0.106		0.112	
	(0.133)		(0.132)	
Firm Size (B)	0.000		0.000	
	(0.002)		(0.002)	
Female Name Score	-0.002		-0.002	
	(0.002)		(0.002)	
Reco. Elite Education	-0.034		-0.043	
	(0.067)		(0.066)	
Reco. Count	0.003		0.002	
	(0.006)		(0.006)	
Constant	2.460	***	2.611	***
	(0.526)		(0.526)	
Observations	534		534	
Log-likelihood	-2,102		-2,098	

Notes: Unit of analysis is the recommendation. Models contain industry fixed effects with robust standard errors, clustered at the audience-member-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Chapter 3

Pursuing Quality: How Search Costs and Uncertainty Magnify Gender-based Double Standards in a Multistage Evaluation Process

3.1 Introduction

Evaluations have a significant impact on important economic outcomes, such as hiring (Fernandez and Fernandez-Mateo 2006), but they are often more of an art than a science: evaluators frequently lack objective information on which to base their assessments and may rely on accessible indicators of expected quality when actual quality is uncertain (e.g., Kovács and Sharkey 2014; Podolny 1993, 1994; Simcoe and Waguespack 2011; Stuart, Hoang, and Hybels 1999). Because ascriptive characteristics such as gender are associated with widely held status beliefs and performance expectations, evaluators often rely on gender as one such indicator of quality (Becker 1957; Berger 1977; Correll and Ridgeway 2003). Therefore, because men are generally more highly valued and perceived as more competent than women (Berger 1977; Correll and Ridgeway 2003), this reliance on gender often leads to a female disadvantage (or male advantage) (Correll and Benard 2006; England et al. 1994).

Research on double standards, a status-based theory of discrimination, indicates that gender is incorporated into evaluations even when information about quality is readily available (e.g., Foschi 1996). Lab-based studies largely show that when presented with similarly performing male and female candidates, evaluators exhibit a preference for men (e.g., Foschi 1989; Foschi and Valenzuela 2012). Scholars argue that women are held to unfairly higher or stricter standards in evaluations, such that they must outperform men with similar qualifications or performance levels to receive comparable evaluations and accolades (see Foschi 2000, for a review). The standards used to judge ability are therefore thought to play a key role in perpetuating social and economic inequalities.

Although this experimental research has been foundational in establishing theory and providing initial empirical evidence for gender-based double standards (e.g., Foschi 1989), the extent to which gender is incorporated into evaluations in organizations and markets remains unclear. Because lab-based studies are unable to simulate the conditions commonly facing evaluators, it is plausible that the double standards problem has been overstated. In lab-based studies, evaluators do not face the competitive pressures typically present in organizations and markets where evaluators are motivated to suppress biases and identify the highest-quality candidates. Also, evaluators in these studies are novices, who may not be equipped to assess candidates along the dimensions for which they have objective information, so they may rely more on unrelated status characteristics, such as gender. To understand how gender affects the evaluation process outside the lab, we provide a field-based test of theory on double standards.

Specifically, we use unique data from a private online platform on which buy-side (e.g., hedge fund, mutual fund) investment professionals openly share relevant investment recommendations to buy and short-sell stock. We analyze a multistage evaluation process on this platform for 3,520 investment recommendations over a six-year period (2008 to 2013). This setting is well-suited for uncovering whether, and to what degree, gender-based double standards are activated in organizational and market contexts for a number of reasons. One chief benefit of this setting is that these investment professionals are motivated to identify quality, making reliance on factors unrelated to quality, such as gender, less likely. Thus, our study can reveal the extent and conditions under which gender-based double standards affect evaluations in a market context.

3.2 Status-based Explanations of Gender Inequality in Evaluations

Across a wide range of organization and market contexts, evaluators are tasked with assessing a set of actors or their products with the explicit goal of selecting the highest-quality options. Job applicants are evaluated by hiring managers in organizations (Fernandez and Fernandez-Mateo 2006), securities and associated firms are assessed by investors and analysts in financial markets (Zuckerman 1999, 2004), and books, films, and music are appraised by consumers and critics in cultural markets (Kovács and Sharkey 2014; Salganik, Dodds, and Watts 2006). A persistent challenge evaluators face is that the actual quality of the options being compared is not easily observable, forcing them to rely on accessible, and often less relevant, indicators of expected quality (Kovács and Sharkey 2014; Merton 1968; Podolny 1993, 1994; Simcoe and Waguespack 2011). Thus subjectivity often enters into evaluation processes: recent causal evidence shows that ratings are sometimes driven by attributes completely unrelated to underlying quality (e.g., Muchnik, Aral, and Taylor 2013).

The *art* of evaluative processes, along with the fact that evaluations have a significant impact on important economic outcomes, has spurred a long tradition of research questioning whether evaluations contribute to systematic disadvantage for certain groups (Bertrand and Mullainathan 2004; Brooks et al. 2014; Foschi 1989; Foschi and Valenzuela 2012). Status characteristics theory, a status-based theory of discrimination, posits that advantages for members of higher-status groups, such as whites and men, emerge because evaluators have higher performance expectations for those individuals. An observable social distinction, such as gender, becomes a status characteristic when it is attributed to a widely held cultural belief that actors with one category of the characteristic, such as male, have greater competence and social value than actors with an alternate category, such as female (Berger 1977; Berger, Rosenholtz, and Zelditch 1980; Wagner and Berger 1993). Because status characteristics carry these performance expectations, evaluators, either consciously or not, may use these characteristics when assessing candidates (Correll and Benard 2006). As a result, actors with the higher-status state of the characteristic (male) benefit from social advantages relative to actors with the lower-status state of the characteristic (female) (Webster and Hysom 1998). Status characteristics research has shown that evaluators generally expect men to be more competent and to have more influence over others in a group than women, and thus their performances are evaluated more positively than those of their female counterparts (Ridgeway and Correll 2004; Ridgeway and Smith-Lovin 1999). To the extent that ascriptive characteristics become imbued with status (Ridgeway and Correll 2000), it follows that associated gender-based performance expectations inform evaluations about candidates when actual quality is uncertain or indeterminate.

Research on double standards, a theory within the status characteristics tradition, furthers this line of inquiry by showing that status characteristics such as gender affect assessments of competence even when performance information is readily available (Foschi 1989). The term "double standards" refers to there being different standards, or "norms defining requirements for the inference of an attribute, such as the level of performance considered necessary to conclude that a person is competent," used to evaluate individuals (Foschi 2000: 22). Gender-based double standards exist when stricter standards are used to measure success for women than for men (Foschi and Foddy 1988), disadvantaging women relative to similarly performing men (Foschi 1989). As a result, women must *outperform* otherwise similar men to receive comparable evaluations and accolades. For instance, requiring a score of 80 percent for women to pass an exam but only a score of 70 percent for men would be an example of a double standard, albeit a blatant and unlikely one in reality. To the extent that women are systematically evaluated using stricter standards, they will be perceived as being less competent than otherwise similarly performing men (Foschi 1989).

3.3 Bringing Double Standards to the Field

The extent to which double standards shape gender inequality in organizational and market settings is unclear, in part because extant experimental research has not been able to mirror the competitive pressures that commonly influence behavior outside of the lab. Economic theories of discrimination posit that evaluations based on attributes not directly related to productivity will be inefficient in competitive markets, such that bias will be competed away (Altonji and Blank 1999; Arrow 1971; Becker 1957; Charles and Guryan 2008). Thus evidence of double standards stemming from lab-based studies may be at least partly due to evaluators in these studies being insufficiently motivated to identify the highest-quality candidates. Also, the participants serving as evaluators in lab-based studies are typically inexperienced in the domain in which they are assessing candidates. More-experienced evaluators may rely on status less than novice evaluators because the former are better at discerning quality (Jensen 2006). As a result, the extent to which evaluators apply double standards may be overstated in lab-based research.

Developing a more-precise theory about when and how double standards in evaluations perpetuate gender inequality requires conducting field studies examining the extent to which more-experienced evaluators apply double standards when they are motivated to identify true quality. Through this form of scientific inquiry will we be able to develop effective solutions to redress gender inequality in groups, organizations, and the economic sector. In light of existing evidence, we predict that our field study will show that double standards are generally applied in evaluations, such that:

Hypothesis 1: *When male and female candidates are being compared by an evaluator, women are less likely to be selected than similarly performing men, on average.*

3.4 Boundary Conditions of Double Standards

Despite evidence that double standards result in different evaluations for similarly performing men and women, it is not clear that they are applied ubiquitously. More-general status theories predict, and subsequent empirical evidence supports, that status is most apt to be factored into the evaluation process when search costs and uncertainty are heightened, because under such conditions it becomes more difficult to discern quality (Azoulay, Stuart, and Wang 2014; Gorman 2006; Kim and King 2014; Podolny 1993; Simcoe and Waguespack 2011; Stuart, Hoang, and Hybels 1999). Given that double standards theory is a status-based account of gender inequality, we propose that the propensity for gender-based double standards to be applied is also a function of the search costs and degree of uncertainty facing an evaluator. Specifically, double standards should be more prevalent when an evaluator is tasked with assessing a larger pool of candidates or is presented with fewer pieces of pertinent information.

3.4.1 Search Costs and Double Standards Theory

The search costs that an evaluator faces are largely based on the number of options, or candidates, the evaluator is assessing. The size of the set of actors or objects being considered during any evaluation process varies; in the labor market, for example, the number of applicants to any given position can range from a few to thousands. Ideally, an evaluator would be able to commit sufficient attention to assess each candidate using all available pertinent information, but search costs increase as the pool of candidates grows, making this approach infeasible. When search costs are heightened, it is logical to expect that evaluators will rely on indicators of quality, such as status signals, to determine which candidates warrant more careful attention, and recent empirical evidence supports this view (e.g., Simcoe and

Waguespack 2011). Consistently, other research has shown that reliance on stereotypical information is more apt to occur under conditions of increased cognitive load, which is more likely when evaluators face heightened search costs (Biernat, Kobrynowicz, and Weber 2003).

If evaluators are selecting from a large number of candidates who perform similarly, it is more likely that they will use gender as a means of sorting, or simplifying the evaluative process, to decide whom to give further attention. A similar logic likely applies to the conditions under which double standards will be activated in evaluations. To the extent that gender is a status characteristic and is used for sifting through large amounts of information, we would expect the prevalence of double standards disadvantaging women to be a function of search costs, such that:

Hypothesis 2: *The female disadvantage in evaluations is strongest when an evaluator is faced with higher search costs.*

3.4.2 Uncertainty and Double Standards

The degree of uncertainty facing evaluators varies across stages of the evaluation process due to shifts in the availability of pertinent information. The process of evaluation is commonly multistage, with an attention stage during which a subset of candidates is selected for further consideration, and a subsequent feedback stage, when members of this reduced set are evaluated more closely and given feedback (Gensch 1987; Häubl and Trifts 2000; Kovács and Sharkey 2014; Simcoe and Waguespack 2011). Generally, the amount of pertinent information available increases as a candidate progresses through these stages, such that uncertainty is reduced in later stages of evaluation. For example, a hiring manager has application and résumé information in the first stage but also gains access to relevant information about a candidate's quality through interviews or screening tests in later stages of the hiring process.

This variation in the amount of available pertinent information across stages makes it imperative to examine whether the effect of gender varies based on the degree of uncertainty facing an evaluator.

In examining the role of status in evaluative outcomes, however, research has commonly focused on a single stage of the evaluation process (e.g., Brooks et al. 2014; Foschi, Sigerson, and Lembesis 1995; Foschi and Valenzuela 2012). For example, hiring audit studies have shown that applicants' names and other signals suggesting gender or race lead to a status advantage for men and whites in the attention stage of evaluation (Bertrand and Mullainathan 2004; Neumark, Bank, and Nort 1996; Pager, Bonikowski, and Western 2009). Some more-recent research has noted the importance of looking across evaluation stages, suggesting that advantages to higher-status actors may not be present in stages at which more pertinent information is available (Castilla 2008; Simcoe and Waguespack 2011; Kovács and Sharkey 2014). Kovács and Sharkey (2014) examined the feedback stage of evaluation, during which evaluators have firsthand information about quality, to show that after winning awards books actually received lower ratings. Although they were unable to look across stages directly, the authors highlighted the interdependence between stages of evaluation, arguing that this decline in ratings is most likely due to a shift in audience composition in the attention stage of the evaluation process—as books gain attention from a broader audience.

Though informative, this snapshot approach is not able to directly assess how variation in the degree of uncertainty affects the likelihood of double standards across stages of the evaluation process. Research has shown that status effects are most pronounced when uncertainty is high (Azoulay, Stuart, and Wang 2014; Gorman 2006; Kim and King 2014; Podolny 1993, 1994, 2005), so we expect double standards to be less prevalent when evaluators face less uncertainty. As the availability of pertinent information is generally expected to increase in subsequent stages of the evaluation process, particularly when the evaluator is constant across stages, we would expect that evaluations become increasingly based on the available objective criteria as a candidate progresses from the attention to the feedback stage. Thus evaluators will be less likely to employ double standards, or to base assessments on gender, when evaluating candidates in the subsequent stage, such that:

Hypothesis 3: *The female disadvantage in evaluations is attenuated in later stages of the evaluative process as the evaluator gains access to additional pertinent information.*

3.5 Empirical Context

The setting for this study is the Real Investors Club (RIC, a pseudonym), a private online platform that brings together buy-side (e.g., hedge fund, mutual fund) investment professionals who share knowledge about market opportunities through recommendations to buy or sell stocks. An investment recommendation submitted on RIC is added to the repository of all previously submitted recommendations and can be selected by other RIC members for viewing and subsequent feedback. Thus, in this context, each investment professional may act both as a recommender, writing and submitting recommendations to be viewed by others, and as an evaluator, evaluating recommendations submitted by others.

We collected unique data from RIC on the investment professionals using this platform, the recommendations submitted, and detailed evaluations of each recommendation over the six-year period from 2008 to 2013. In addition to this quantitative data, which we used to test our hypotheses, we conducted 21 semi-structured interviews ranging from approximately 20 minutes to nearly two hours with 19 investment professionals, 12 of whom are RIC members. The interviews revealed that most members did not know any other members on the platform before joining RIC. Of those who mentioned knowing others on RIC, they reported having known only a few of the thousand-plus members before joining. Thus the evaluation process is unlikely to be affected by prior knowledge about others on this platform.

Recommendations include a price target, or the price the recommender forecasts that the security (stock) will reach in the future, and the investment horizon, or the length of time the recommender expects it will take for this price target to be reached (e.g., one year). In addition to submitting a buy or sell recommendation, the recommender includes a detailed justification supporting this position.[1] The detailed justifications average over 1,400 words, and, though their content varies, they generally include a summary of supporting information gleaned from company reports (e.g., quarterly reports), a discussion of macroeconomic trends, and a discussion of the valuation technique used (e.g., models).

This setting allowed us to conduct a field-based test of double standards theory and to identify the conditions under which double standards are most likely to enter into evaluations, for three reasons. First, evaluators in this setting are motivated to select the highest-quality recommendation and are thereby incentivized not to discriminate. This point was highlighted during interviews, in which investment professionals using RIC made it clear that they are time constrained and focus on identifying the recommendations that they expect to yield the greatest returns. Second, evaluators in this context are equipped with the expertise necessary to properly assess quality. Each RIC member is an investment professional who analyzes investment opportunities daily. Third, evaluators face varying degrees of search costs and uncertainty in the evaluative process, which allowed us to examine how these aspects affect the propensity for gender-based double standards to be used. RIC evaluators may assess recommendations when there are few (i.e., low search costs) and many (i.e., high search costs)

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[1] Recommenders are also given an option to submit a recommendation with a much shorter justification (for a discussion of this process, as well as the motivation to engage in this knowledge sharing, see Botelho 2016). Recommendations are separated by justification type, and only those recommendations that include a detailed justification undergo evaluation; therefore the sample for our analyses is limited to this subset of recommendations.

other recommendations from which to choose, and the degree of uncertainty in their two-stage evaluative process is lower in the second (feedback) stage, as we discuss below.

Additionally, this setting preserves several important strengths of lab-based studies that are commonly difficult to achieve in the field. First, in this context the men and women being evaluated are competing directly with one another. Double standards is a popular explanation offered for observed gender differences in evaluative outcomes, but it is difficult to conclude that gender biases are driving observed differences without comparing evaluative outcomes for men and women who are in direct competition, such that their performances are directly comparable. Second, in financial markets, performance is unbiased: if two individuals simultaneously take the same action, their performance outcome will be the same, regardless of ascriptive characteristics such as gender. Lab-based studies achieve this by artificially providing identical performance information for the candidates being compared, but it is difficult to achieve in market and organizational settings.

3.5.1 Stages of Evaluation

When investment professionals on RIC are not acting as recommenders, they may act as evaluators and serve as the audience for the recommendations submitted by others. Recommendations are evaluated in two stages. The first, or attention, stage occurs when the evaluator assesses whether a given recommendation is worthy of further consideration. Evaluators make this assessment by deciding whether to click on and view the recommendation details (i.e., give it attention) based on a limited amount of information. In the attention stage, recommendations are listed in reverse chronological order. Evaluators can see the firm name for the stock being recommended, the recommendation (e.g., long versus short), and the return since the recommendation was submitted, as well as the recommender's name and his or her employer's name. To facilitate the search for recommendations, evaluators can also screen recommendations based on objective criteria, such as industry, firm size (market capitalization), and expected return.

For an evaluator to access comprehensive information about a recommendation, he or she clicks on the recommendation and enters the second, or feedback, stage of the evaluation process. In this stage, the evaluator can see all of the information available at the attention stage, as well as a detailed justification supporting the recommendation, which usually includes an analysis of key information from meetings with management and investor calls, recent news, company financial reports, competitors, and projections and a valuation for the stock being recommended. The evaluator can then choose to rate the recommendation numerically along two dimensions—the quality of the analysis (justification rating) and the expected return (return rating, which was added to RIC later in the period of our study)—and to provide freeform comments or questions on the recommendation. The justification rating is intended to measure whether the detailed justification for the recommendation includes relevant and well-thought-out analyses supporting the recommendation and was referred to by one interviewee as the "good analyst rating," demonstrating an intimate link between the quality of a recommendation and its recommender. Other interviewees frequently discussed the importance of a well-presented analysis in both supporting a recommendation and indicating the recommender's skill. The return rating measures the evaluator's belief that the recommendation (e.g., buy versus sell) and the magnitude (e.g., price target) are correct and likely to be achieved. Comments are freeform entries that allow evaluators to leave feedback on or reactions to the recommendation. Recommenders are unaware of who has given them attention (clicked on) or rated their recommendations, but they can see who has commented on their recommendations.

Investment professionals we interviewed stated that their goal was to identify high-quality recommendations that could help them improve their performance. Although a few of the interviewees said that they constrain their searches to certain industries or firms, most claimed not to restrict their searches to a specific screening protocol. These interviewees also stated, however, that they were less likely to take action (buy or sell) on a stock outside of their area of coverage.

Most interviewees stated that they inferred a recommender's gender from the name listed on the recommendation. One interviewee said, "When I see a name like Mary it sticks out because there are so few [women] in this industry." Most interviewees said that gender did not enter into their consideration when choosing a recommendation to view. The decision to give more attention to a particular recommendation was based solely on its potential to generate profits. As one industry insider stated, "I am in the business of making money, I don't care who you are, as long as you can help me in that goal." But another insider had a different viewpoint: "Whoever says there is no bias against females in this industry is bullshitting you." By examining the extent of gender-based differences across this multistage evaluative process, we were better able to unpack whether, and under what conditions, gender affects evaluations despite pertinent information on performance being freely available to the evaluator.

3.5.2 Performance

To better understand the role of double standards in evaluations, it is important for performance to be standard, determined by an unbiased mechanism, and freely available to an evaluator. A standardized performance measure helps ensure that information is conveyed and interpreted similarly by all evaluators; for the performance metric to serve as an indicator of quality, the vast majority of the evaluators in the setting must agree on what constitutes a good versus a bad performance. An unbiased performance metric means that any two actors taking the same action must receive the same performance outcome. An underlying bias in the attribution of performance would confound the results, such that what appears to be a double standard may actually be the result of bias in properly assessing performance. The performance metric must also be freely available to the evaluator so that the evaluator does not have to incur additional costs to access this information. Without such a performance metric, it is difficult to rule out that reliance on ascriptive characteristics is due to a lack of other indicators of quality.

The investment industry, and RIC in particular, provides a setting well suited to this analysis given the standard, unbiased, and visible nature of performance here. Performance in the investment industry is measured as the rate of return on a given investment (R_t) and is calculated as $R_t = \frac{(p_t - p_{t-1}) + d_t}{p_{t-1}}$, where p_t is the price of the stock at time t; p_{t-1} is the price of the stock at the start of the investment horizon; and d_t accounts for the sum of any distributions (e.g., dividends) between t-1 and t. Few processes are as unbiased as a stock's performance, which is accorded by the stock market, making this a strength of our setting. If any actor, regardless of ascriptive characteristics, takes a certain position in the market, his or her performance would be identical to that of any other actor who took this position at the same time. Performance being visible means that evaluators can observe how a given recommendation is performing before deciding whether to view the recommendation, which is the case across both stages of evaluation in our setting.

A difficulty of translating a theory from the lab to the field is a loss of perfect control over the setting. For example, double-standard studies in the lab have manipulated performance perfectly, which ensures that the individuals being evaluated are performing identically at all times. This is difficult for any empirical test of double standards and is also unrealistic. But although we control for performance in our analyses, a benefit of this setting is that there is no **ex ante** reason to expect that either gender systematically outperforms the other. During the period under study, the difference in the average performance for recommendations submitted by self-identified men versus women is only .17 percentage points, with women outperforming men, but this difference is neither substantively nor statistically significant ($p =$

.97). This return was calculated from the closing price on the day before the recommendation was submitted to approximately the end of the investment horizon, as stated in the recommendation, or until the end of 2014, whichever occurred first. If the recommendation was made after the market was closed, the closing price on the day of the recommendation was used.

3.6 Data

We collected data from RIC from 2008 to 2013, and we used external financial databases to collect data on the firms and stocks featured in the recommendations. We used financial market data from the Center for Research in Security Prices (CRSP) to calculate performance and firm size, and industry data are from Compustat. Only recommendations pertaining to firms listed on a U.S. exchange (e.g., NASDAQ or NYSE) and involving common stock—as opposed to debt or options—were analyzed in this study. Further, the stocks recommended had to be in the CRSP database and have at least two months of return data. This study focuses on 3,520 recommendations meeting these criteria, submitted by a total of 1,550 recommenders. On average, each recommender submitted 2.27 recommendations during this six-year span. This engagement is low for a few reasons. Investment professionals on this platform are value investors and do not take new positions regularly. Further, they do not share every recommendation they are considering, and they focus on investments they have actually made (see Botelho 2016, for more detail on motivations to share this knowledge). But variation in terms of engagement does not affect the research question addressed in this study, as an investment professional's gender does not affect his or her level of engagement on RIC. Further, a feature of lower levels of engagement is that factors such as reputation, based on prior recommendations, are much less likely to play a role in our analyses.

For analysis, we collected detailed data on the characteristics of both the recommender and the recommendations to isolate the existence of a double standard at both the attention and feedback stage of this evaluative process. Further, to rule out a common alternative explanation—that observed gender differences are due to women acting in a manner that is systematically different from their male counterparts (e.g., Baldiga 2013; Bromiley and Curley 1992; Ding Murray, and Stuart 2006; Fernandez-Mateo 2009)—we also collected and analyzed measures of risk aversion. Lastly, we were able to rule out that unobservable differences between men and women are driving our results.

3.6.1 Dependent Variables: Evaluative Outcomes

For the attention stage of the evaluation process, our analysis focused on identifying whether there are gender differences in the propensity for recommendations to be viewed. We measured this using the outcome variable *number of views*: the number of times a recommendation was "clicked on," or selected, in the attention stage. For the feedback stage of the evaluation process, our analysis used three measures of evaluative outcomes: the *justification rating*, *return rating*, and *number of comments*. Each rating is measured on a 0–5 scale.[2] The justification rating assesses the quality of the analysis, whereas the return rating assesses the likelihood that the recommendation will reach its price target. Each variable measures the respective average rating received from all evaluators. Evaluators can also leave comments, with the primary purpose of asking questions or offering critiques. We measured the total number of comments a recommendation received from the time the recommendation was submitted through the end of the study window.[3]

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[2] Initially, ratings could be submitted in half-point increments, but the system was changed near the end of the study period to allow only integers. This change does not affect our results because we are analyzing the average rating. All results are robust when recommendations after this change are excluded.

[3] We also investigated the valence of the comments left, in terms of neutral (inquiries) versus negative comments. A random sample of 1,000 comments suggested that comments are overwhelmingly neutral (97 percent); only 29 comments had a negative valance, and most of these comments were classified as blunt questioning rather than truly negative. There are no differences in terms of the recommender's likely gender. We thank an anonymous reviewer for this suggestion.

3.6.2 Independent Variable: Gender

At both stages of evaluation on the RIC platform, the gender of the recommender is not directly noted. Evaluators are able to infer gender from the recommender's name, which is visible in both stages. RIC members are not required to identify their gender, and only about 48 percent do; men and women are equally likely to do so. Although anyone could search for this information (e.g., using the individual's name and an online search engine), investing the time to do so seems unlikely in this context. Inferring individual-level ascriptive information from a name is common practice in social science research (e.g., Bertrand and Mullainathan 2004; Neumark, Bank, and Nort 1996) and is a natural approach in this case, given the data-generating process: for an evaluator to incorporate a recommender's gender into an assessment, he or she first needs to infer gender from the recommender's name. To assign gender to each RIC member, we used a naming algorithm, the IBM InfoSphere Global Name Management Tool, and scored each recommender's name based on the likelihood of it being a woman's name. This tool takes as its input an individual's first name and compares that name with its database of 750 million names from around the world (Maguire 2012). Each name is then scored, on a scale from 0 to 99, for the likelihood that the individual with the given name is female: as this score increases, the likelihood that the name is a woman's increases. All of our results are robust to using a dichotomous gender variable using a female name score of 12 as the cut-off, with names scoring less than 12 coded as male and those scoring 12 or greater coded as female. The cutoff of 12 was chosen because none of those investment professionals who self-identified as female had a female name score of less than 12.

This measure was operationalized as the variable female name score. Figure 1 is a histogram of the names on RIC, and figure 2 provides a more detailed look at the distribution of names by focusing on the distribution of female name scores greater than 0. Given the low representation of women in the investment industry (National Council for Research on Women

2009), it is not surprising that most names in our sample are associated with men (88.55 percent have a score less than 12), and only 4.48 percent of the names are more likely to be female than male (i.e., the name received a score higher than 50). The effect of this variable across our models helps us determine whether a double standard is present in the evaluation process and the degree to which uncertainty affects the propensity for double standards to come into play.

[Figure 1]

[Figure 2]

3.6.3 Control Variables

We included both recommender- and recommendation-level characteristics as controls. We attempted to control for the variables that are visible to an evaluator when assessing a recommendation at a given stage of the evaluation process, as well as other variables that could indirectly affect that process. At the recommender level, these include measures for education, the rank of undergraduate and graduate institutions the recommender attended, location, and the number of recommendations submitted before the focal recommendation. We used the 2013 *U.S. News* College Ranking (*U.S. News and World Report* 2013a) for recommenders' undergraduate institutions and the 2013 *U.S. News* MBA Ranking (*U.S. News and World Report* 2013b) for their graduate institutions. For non-U.S. business schools, we used the 2013 *Financial Times* Global MBA Ranking (*Financial Times* 2013). Recommenders' educational institutions were grouped into elite undergraduate and graduate (for a ranking of 1–20) because recommenders with high-status affiliations may attract different types of evaluations. To control for location, we used two dichotomous variables: major city and non-U.S. location. *Major city* represents all cities where 2 percent or more of recommenders are located and is coded 1 for all recommenders from those locations. These cities include the major financial hubs in the U.S., such as Boston, Chicago, New York, and

San Francisco. The variable *non-U.S.* is coded 1 for all recommenders located in a city outside of the U.S. Location is an important control because an investment professional's ability to work in certain locations, such as financial hubs, may be a signal of quality or legitimacy for evaluators.

At the recommendation level, we controlled for recommendation type, investment horizon, investment style, firm information about the focal stock, and performance, as these factors may affect the evaluation process. *Short position* takes a value of 1 if the focal recommendation is to short-sell a stock and a value of 0 if the recommendation is to buy. Short-selling is the practice of selling borrowed shares of a stock with the guarantee of purchasing and later returning these shares to the lender along with any distributions, such as dividends. *Short investment horizon* takes a value of 1 when the recommendation has an investment horizon of less than one year and 0 if the investment horizon is greater than one year.

The investment style of the recommendation is self-reported and is broken into four indicator variables: *growth*, *value* (our reference category), *event* (e.g., merger and acquisition), and *other*. For firm information, we included controls for firm size (measured as market capitalization: price per share × shares outstanding) and industry fixed effects. For industry, we used the 24 two-digit North American Industry Classification System (NAICS) sectors and an indicator for a missing NAICS sector. Performance controls include *expected return* $(\frac{\textit{price target} - \textit{price at recommendation}}{\textit{price at recommendation}})$ and *week-one performance*, measured as the return of the focal recommendation in the first week after being submitted, minus how the market (S&P 500) performed during the same period—in other words, the degree to which the recommendation outperformed (or underperformed) the market during this period. We used a recommendation's first week of performance because recommendations receive more than 50 percent of views within the first five calendar days after being submitted, with a long right tail in the distribution.[4]

Table 1 provides summary statistics for each of the variables used in our analyses. Although our analyses leverage the continuous measure *female name score*, we report the descriptives of the data in two panels to allow for a visual comparison of those investment professionals more likely to be classified as female than as male: panel A includes summary statistics for recommendations from recommenders whose female name score is less than 12, and panel B includes summary statistics for recommendations from recommenders with a *female name score* greater than or equal to 12. A formal test for statistical significance of the differences by gender (panel A versus panel B) in terms of each control measure revealed that only differences in *elite undergraduate education* and *short investment horizon* were significant ($p < .05$). A chi-squared test revealed no significant difference in the distribution of industry choice by gender ($p = .169$). This strongly supports that key observable characteristics related to recommendation choice do not differ between men and women in this context. Table 2 is a correlation table.

[Table 1]

[Table 2]

3.7 Results

We began our empirical analysis by estimating the effect of a recommender's gender, inferred from his or her name, on a given recommendation's viewership in the attention stage of the evaluation process. Given that the main dependent variable, *number of views*, is a count variable, we estimated a negative binomial regression. For the feedback stage of the evaluation process, we used the dependent variables *number of comments*, *justification*

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[4] All results are robust to using longer performance windows.

rating, and *return rating*. We estimated the number of comments with a negative binomial regression, and we estimated the justification and return ratings with an ordinary least squares (OLS) regression. All models control for time fixed effects, at the year level, as well as industry fixed effects. Robust standard errors are clustered at the recommender level given the possibility that viewership may be correlated within recommender. Our ability to mimic the data-generating process of inferring gender from a name while also controlling for the information that evaluators claim to use in this context allows us to identify the prevalence of double standards in evaluations.

3.7.1 Is There a Female Disadvantage?

To understand whether there are double standards in the attention stage of evaluation, we examined whether investment recommendations submitted by recommenders with names more likely to be identified as female receive fewer views. In Table 3, we predict the number of views that a given recommendation receives. We find that gender significantly affects the evaluation of recommendations in the attention stage: for each 1-point increase in female name score, the difference in the log of number of views decreases by .0025 units ($p <$ .001), translating to approximately a .25-percentage-point decrease. For example, a recommendation submitted by an individual named Bowen (with a female name score of 60) receives about 15 percent fewer views than a recommendation submitted by someone with the name Matthew (with a female name score of 0). For recommenders with the most female-typed names, the penalty is more substantial: a recommendation submitted by an individual named Mary (with a female name score of 99) receives about 24.8 percent fewer views than a recommendation submitted by Matthew. Additionally, performance is a key screening metric, as the positive coefficient of week-one performance (Model 1B, $p < .05$) reveals. Therefore we find strong support for hypothesis 1. There is evidence of a double standard disadvantaging women in the attention stage of the evaluation process, such that recommendations submitted by women are significantly less likely to receive attention than those submitted by similarly performing men.

[Table 3]

3.7.2 Double Standards, Search Costs, and Uncertainty

To test hypothesis 2—that the effect of the female name score will be strongest in times of increased search costs—we operationalized search costs using the number of recommendations being considered during the attention stage. Using an approximately year-long subset of microdata capturing evaluators' viewing habits, we found that recommendations receive more than 50 percent of views within the first five days of being submitted and that the distribution has a very long right tail. We constructed the measure of traffic to capture the total number of recommendations submitted in the five days before and after a focal recommendation was submitted and used two dichotomous variables, *low-traffic* (i.e., low search costs) and *high-traffic* (i.e., high search costs), to represent whether the focal recommendation was submitted during a low-traffic (bottom decile) or a high-traffic (top decile) period.

As Model 2A in Table 4 reveals, a given recommendation receives fewer total views (10.6 percent fewer) when submitted during a high-traffic period and more total views (11.5 percent more) when submitted during a low-traffic period, relative to recommendations submitted during the reference group ($p < .01$). We found no evidence that gender influences when a recommendation is submitted: those with a more-female name are no more likely than those with a more-male name to submit a recommendation during high-traffic (or low-traffic) periods (9.9 vs. 9.1, $p = .610$).[5] Therefore, any observed gender differences in the attention stage

[5] Recommenders with a female name score less than 12 were compared with recommenders with a female name score greater than or equal to 12 (similar to Table 1).

are not being driven by systematic gender differences in the level of competition for attention facing submitted recommendations.

[Table 4]

To directly test hypothesis 2, we examined whether the observed average female penalty varies based on traffic. We found marginal evidence ($p = .076$) that the effect of a higher female name score in the attention stage is magnified in times of increased search, or in high-traffic periods (Table 4, Model 2B). Conversely, in low-traffic (low-search) periods, the non-significant interaction effect (Table 4, Model 2B) suggests that there is no difference in the female penalty relative to the reference group. Together these results provide suggestive evidence that gender factors into evaluations as a sorting mechanism during times of increased search costs, during which evaluators are less likely to devote attention to each option.

We tested hypothesis 3 by focusing on the feedback stage of the evaluation process, during which evaluators face less uncertainty as they gain access to additional pertinent information on which to base their evaluations. At this stage, evaluators may comment on and rate recommendations that they have selected to view. The results are shown in Tables 5 and 6. Overall, we found support for hypothesis 3. Conditional on a recommendation being viewed, gender does not play a role in the number of comments (Table 5, Models 3A and 3B), the justification rating (Table 6, Models 4A and 4B), or the return rating (Table 6, Models 5A and 5B) received in the feedback stage. Beyond these results being statistically insignificant, their economic significance is essentially zero. For example, a recommendation submitted by someone with a female name score of 99 would receive a return rating approximately .08 lower than a similar recommendation submitted by someone with a female name score of 0. To illustrate the magnitude, this difference represents only 2.3 percent of the mean value of return rating (3.44). Therefore, once an evaluator chooses to give attention to a recommendation, the gender of the recommender does not affect subsequent evaluations in the feedback stage.

[Table 5]

[Table 6]

3.7.3 Evidence of a Stricter Standard for Women

To better understand how the standards being used to assess men and women differ, a logical next question is how much do women have to outperform men to receive a similar number of views as the average man? We found that recommendations submitted by investment professionals with more-female names receive the mean level of attention only when their performance is in the top quartile. But at this performance level men still receive more views, such that the gender difference persists. Our evidence suggests that women receive equal attention as similarly performing men only when their performances are in the top decile: all of the highest-performing recommendations, irrespective of female name score, receive the same level of attention. This provides direct evidence that women are generally held to a stricter standard than men during the attention stage of the evaluation process.

3.7.4 Biased Evaluators Opting Out of the Evaluation Process

We addressed the possibility that an alternative to our proposed mechanism of a reduction in uncertainty is driving our finding that a gender difference exists in the attention stage of evaluation only. We argued that this result is driven by the introduction of additional pertinent information in the feedback stage that reduces uncertainty, but our identification strategy assumes that biased evaluators are not simply selecting out of this stage of the evaluation process by not clicking on recommendations submitted by women in the previous attention stage. To the extent that status-based discrimination is contributing to a preference for male candidates in the attention stage, those with the strongest biases against women or preferences for men would be more likely to exclude women from the consideration set in this first stage. As a result, it is plausible that the evaluators who are most apt to assess female candidates in the feedback stage are those with either weaker or nonexistent gender biases.

To rule out this alternative, we identified those recommendations that all evaluators, irrespective of their biases, are most apt to click on in the attention stage.[6] We did this by identifying industries for which the fewest number of recommendations are submitted on RIC and then replicating the analyses presented in Tables 3, 5, and 6 using this subset of our sample; see Table 7. The logic for this analysis is that although biased evaluators may still ignore women's recommendations, they are least likely to do so for these underrepresented industries on RIC. If evaluators seek information about firms in these industries, they are more likely than other evaluators to give attention to recommendations submitted by those with higher female name scores due to the scarcity of options.

[Table 7]

In our analysis on this subset, we found no evidence of a statistical or substantive gender difference in the number of views that a recommendation receives (Table 7, Model 6A). This result suggests that our assumption is correct that evaluators who seek access to information for industries that are underrepresented on this platform are less likely to use a double standard disadvantaging women in the attention stage than are evaluators more generally. Further, in line with our previous analysis of the feedback stage of evaluation, we found no evidence of a gender difference in terms of comments or ratings among the recommendations in this subsample. Though it is possible that biased evaluators are giving attention to these recom-

[6] We thank an anonymous reviewer for this suggestion.

mendations but refraining from providing feedback, these analyses of underrepresented industries provide more rigorous support that our finding of no gender difference in the feedback stage of evaluation is related to the introduction of additional pertinent information.

3.7.5 Risk Aversion

One possible alternative explanation to the double standards argument for the observed gender difference in the attention stage of the evaluation process is that women are doing something systematically differently. If there are desirable characteristics that are more commonly demonstrated by men than women, this gender difference could be driving what appear to be double standards. Evaluators may show a preference not for men but for certain characteristics more commonly displayed by men that are perceived to indicate future performance (Foschi and Valenzuela 2008).

Although we ruled out many potential sources of systematic gender differences in Table 1, we devoted special attention to risk-aversion behavior given the vibrant debate related to gender differences in risk aversion in the finance industry (e.g., Barber and Odean 2001; Beckmann and Menkhoff 2008; Hinz, McCarthy, and Turner 1997; Jianakoplos and Bernasek 1998; Niessen and Ruenzi 2007; Sunden and Surette 1998; VanDerhei and Bajtelsmit 1997). Our interviews with investment professionals also revealed a preference for higher-risk recommendations. To the extent that evaluations are based on a preference for higher-risk recommendations, and to the extent that women are systematically submitting lower-risk recommendations, observed gender differences in attention could be the result of this preference for risk and not a preference for men *per se*.

It is difficult to unpack the role of gender and risk aversion, because measuring risk attitude at the individual level is empirically challenging (Friedman 1994). Most studies rely on self-reported measures of risk aversion, which may be positively biased, as women have been shown to have greater concerns about violating gender-stereotypical behaviors (Deaux and

Major 1987; Heilman 1980); women may self-report their risk attitudes and preferences in a way that aligns with expectations, even if this is not how they actually behave. This difficulty extends to the investment management industry, in which risk is measured at the fund level, which confounds individual-level decisions with team-based decisions because a fund manager's risk-taking investment behavior may be largely driven by the investment team's perspectives.

Using a comparison of means (Table 1), we did not find any evidence that women act in a more risk-averse way than men on average, but it is also important to assess whether there are systematic gender differences in these measures conditional on other important variables. For this analysis we used three variables from our controls—*short position*, *short investment horizon*, and *expected return* (logged)—as well as a measure of the volatility of the stock's return six months before the recommendation was submitted, *excess return volatility* (logged).

Short-selling is a risky position because a stock's price can rise without an upper boundary, making possible loss infinite. Conversely, the loss associated with a buy position is limited to the amount of the initial investment. Choosing a short investment horizon or a large expected return also proxies for the recommender's risk tolerance: a recommender is more likely to reach his or her price target when the expected return is low and when the investment horizon is longer. By choosing shorter investment horizons and large expected returns, the recommender increases his or her likelihood of being wrong. Additionally, shorter investment horizons have been seen as riskier given that they suggest that the recommendation is exploiting an anticipated market change or condition, as opposed to a long-term view (Barber and Odean 2001). Excess return volatility measures the tendency of the returns, relative to the S&P 500, to rise or fall daily in the six months previous to the recommendation. This measure does not differentiate positive fluctuations (increases in return) from negative fluctuations (decreases in return) and can be seen as the amount of market risk for the stock being recommended. Though no single measure is enough to categorize an actor in terms of risk aversion, evaluating all of these measures together attenuates this concern.

Logit regression results showed an association only between the likelihood of a shorter investment horizon and female name score (.0065; S.E. = .0027; $p < .05$), and this association is the opposite of what we would expect if women were more risk averse than men: recommenders with more-female names tend to recommend investment horizons that are shorter. The other measures of risk aversion provide no support for a link between risk aversion and female name score, neither substantively nor statistically. Thus we conclude that there is at most weak evidence that women may be slightly more tolerant of risk than men in this setting.

Although there is still a valid concern that no single measure is sufficient to categorize one group as more risk averse than another, the lack of consistent evidence across all four of these measures suggests that, in this setting, men and women do not systematically differ in terms of risk aversion. Therefore, although risk is a favored attribute in this context, this alternative explanation does not drive our observation that evaluators prefer recommendations by male recommenders in the attention stage. This result, in conjunction with the lack of differences in Table 1, allows us to rule out endogeneity concerns related to observable systematic gender differences in actions.

3.7.6 Unobserved Gender Differences

Another concern is that unobserved gender differences that cannot be easily measured are driving our results in the attention stage. To address it, we limited our sample to recommendations from those who self-identify as male, the rationale being that an analysis on this subset allows us to indirectly control for unobserved heterogeneity related to gender. As shown in Table 8, when the sample is limited to this subset, our results are robust. We found the same relationship between the recommender's *female name score* and the number of views a recommendation receives: recommendations submitted by men with more-ambiguous or more-female names received fewer views than did those submitted by men with more-male names. This test helps rule out the concern that women on this platform may be acting differently in a difficult-to-measure way. If our results were due to unobserved gender differences, we would not expect to see this female penalty present in an analysis of self-identified men. The fact that men with gender-ambiguous or more-female names received fewer views than did men with more clearly masculine names provides compelling evidence that double standards are being applied in the attention stage of evaluation. This approach provides clean identification of the effect of gender as a persistent signal even when more relevant indicators of quality are present and freely observable. This result also indicates that gender is being inferred from a recommender's name, validating that female name score captures the data-generating process.

[Table 8]

3.7.7 First-name Frequency

Although a strength of the IBM InfoSphere Global Name Management Tool is that it uses a vast and diverse database for its naming algorithm, there may be a concern that the evaluators are less likely to know the probable gender of unfamiliar names. To alleviate this concern, we used the frequently occurring first-name data from the 1990 public-use U.S. Census (U.S. Census Bureau 1990). Approximately 80 percent of the recommenders' first names were matched to these data. We restricted our analysis to recommendations submitted by a recommender having a first name included in this list of popular names and found our results to be robust, as shown in Table 9.

[Table 9]

3.8 Discussion

Evaluation processes are a cornerstone of most market and organizational settings, and their outcomes have significant economic implications. The inherent uncertainty resulting from missing performance information often leads evaluators to rely on status characteristics as indicators of candidates' expected performance or quality (e.g., Azoulay, Stuart, and Wang 2014; Kim and King 2014; Podolny 1993, 2005; Simcoe and Waguespack 2011), making evaluations more of an art than a science. Research suggests that status characteristics, such as gender, affect evaluations even when more-pertinent performance information is available (Bertrand and Mullainathan 2004; Foschi 1989; Foschi and Valenzuela 2012). Yet these studies, largely conducted in the lab, have not established whether double standards disadvantaging women remain when the setting is competitive, evaluators are experienced, and evaluators face varying search costs and degrees of uncertainty.

Using unique data from an online platform on which investment professionals openly share investment recommendations, this study examined whether recommendations submitted by men are favored over those submitted by similarly performing women across a multistage evaluative process. We found that in the attention stage of the evaluation process, recommendations submitted by men are more likely to be viewed than those submitted by women, particularly in periods when evaluators are selecting recommendations from a larger set of options. Although we found a female disadvantage in the attention stage, once men and women are selected into the consideration set we did not find evidence of a female disadvantage in the subsequent feedback stage, when evaluators have access to a large amount of additional pertinent information.

These findings have several implications for research on status-based mechanisms of discrimination and on evaluative processes more generally. First, our study provides direct evidence that double standards lead to unequal evaluation outcomes for similarly performing men and women in organization and market settings. This study provides a field-based test of double standards theory in a setting in which evaluators are well equipped to assess candidates and have a strong disincentive to discriminate. Though lab-based studies have found empirical support for the theory, they have been unable to identify the extent to which double standards persist in the face of competitive pressures and with experienced evaluators. Despite evaluators in this context having relevant and objective performance metrics freely available to them, and despite their being experts in this industry, we find evidence that double standards disadvantaging women persist in the attention stage.

This direct evidence is strengthened because this field-based test of double standards is conducted in a context in which a common alternative explanation for observed gender differences, namely statistical discrimination, is unlikely to be at play. Statistical explanations posit that differences in the treatment of groups are a logical response to the problem of limited information (Arrow 1971; Becker 1957; Phelps 1972): if a valued characteristic is difficult or costly to observe and has different distributions for men and women, treating these groups differently would be rational. In our context, however, pertinent objective information is available and, as we show, there is no gender difference along any observable dimension (e.g., performance, risk aversion, industry choice, or recommendation type). Thus, although we do not claim to falsify or rule out the possibility that statistical discrimination also plays a significant role in perpetuating inequality in some cases, this study adjudicates between these two competing explanations in this context.

Second, this study incorporates more-general status research, which indicates that status-based advantages vary with the degree of search costs and uncertainty (e.g., Azoulay, Stuart, and Wang 2014; Kim and King 2014; Podolny 1993; Simcoe and Waguespack 2011; Stuart, Hoang, and Hybels 1999), to isolate the conditions under which double standards are most prevalent. We find that double standards disadvantaging women are most likely when evaluators face heightened search costs and greater uncertainty stemming from variation in the availability of pertinent information. The female disadvantage we observe is strongest when evaluators are selecting recommendations from a larger set of options. Furthermore, though we find a female disadvantage in the attention stage, once men and women are selected into the consideration set we do not find evidence of a female disadvantage in the subsequent feedback stage, when evaluators have access to much more detailed information about quality and performance. Evaluators are not simply exercising a universal preference for men but are using gender as a status characteristic to address a problem of uncertainty.

Our finding that there is no evidence of double standards in the feedback stage of evaluation does not suggest that double standards do not enter into later stages of evaluation. Rather, our findings show the importance of looking at the conditions surrounding the evaluation process and the limitations of making claims about effects of double standards based on results focused on a snapshot of the evaluative process. We show that the effects of double standards in evaluations are not ubiquitous but depend greatly on the conditions that evaluators face.

This study also provides an upper bound for double standards theory in a competitive setting. We tested the extent to which double standards lead to a female disadvantage in evaluations in the male-typed investment management industry (Alden 2013; National Council for Research on Women 2009), in which gender seems to be particularly salient (e.g., Beckman and Phillips 2005; Turco 2010). We would expect double standards to be prevalent in this context (e.g., Foschi 1989). Our findings showing that double standards disadvantaging women are not ubiquitous in the evaluation process in this male-typed context suggest that the prevalence of gender in evaluations is unlikely to be more pronounced in more gender-neutral or female-typed settings in which experienced evaluators face competitive pressures.

Because this study is based on data from a single context, we must consider limitations to the generalizability of the results. The evaluative process in this context does not seem atypical, especially given that this context brings together a globally diverse set of professionals representing a wide spectrum of investment firms. But this evaluative process is conducted entirely via an online platform, and although online evaluations are increasingly common (e.g., Amazon, Yelp) and have important consequences, to enhance the generalizability of these findings future research could examine gender inequality in contexts in which evaluations use an alternative medium. A different mode of evaluation, for example face-to-face evaluations, may make gender more salient and could either lessen or exacerbate the presence of bias.

We believe that a particularly promising avenue for future research is to further unpack how search costs and uncertainty contribute to bias in evaluative processes and to examine the extent to which evaluations contribute to gender inequality in non-male-typed settings. This requires examining whether double standards exist in multistage evaluation processes in female-typed or gender-neutral contexts when objective performance information is available to the evaluator. Future research might also directly consider how gender differences in the evaluation process stemming from double standards affect subsequent outcomes for men and women. It is difficult to imagine that systematic biases in the evaluation of women or of their work products would not result in penalties in related outcomes for those individuals, but a direct examination of this issue would be productive for understanding the implications of double standards in evaluation processes.

This study also has important practical implications that may inform organizational practices and policy aimed at redressing inequality. Organizations could minimize the signaling of gender and other status characteristics in stages of the evaluation process in which uncertainty is high. Further, increasing the presence of minority groups, such as women, may reduce the salience of status characteristics in evaluations. Platforms such as the one under study, which provide equal access to investment professionals, may play a critical role in achieving this goal. Consistent with this, policymakers have taken measures to increase the number of women in the investment industry, as demonstrated by a report of the Rothstein Kass Institute (2012) highlighting state-level initiatives to increase women's involvement in the investment management industry. Although such prescriptions are unlikely to eradicate gender inequality, they provide a path toward progress.

3.9 Figures and Tables

Figure 1: Distribution of Female Name Score

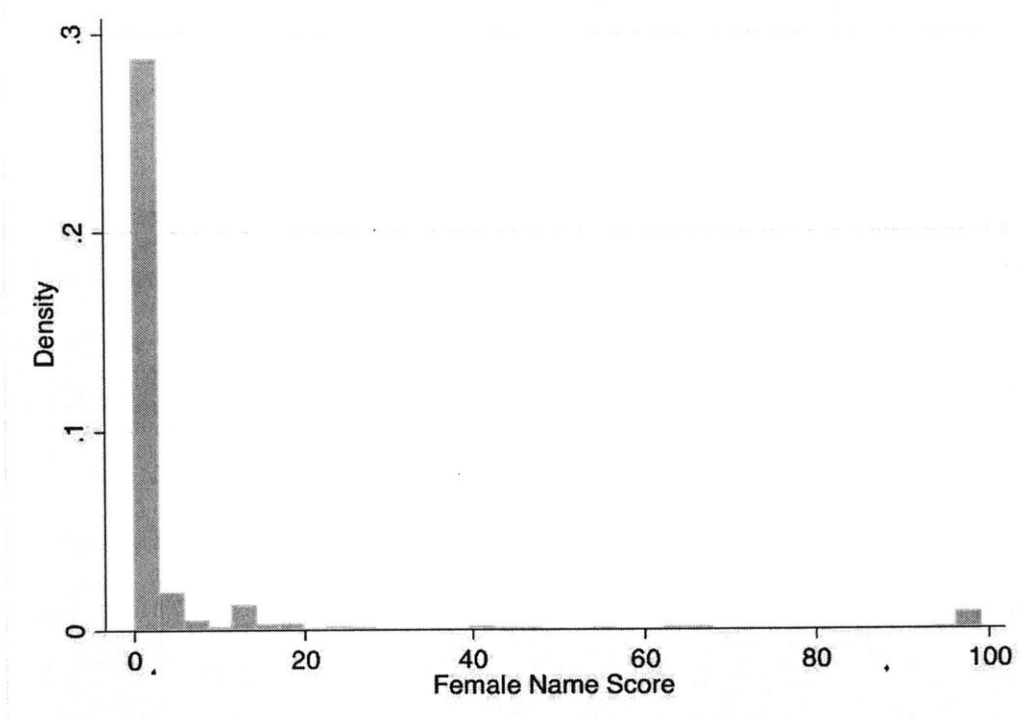

Figure 2: Distribution of Female Name Score Greater than 0

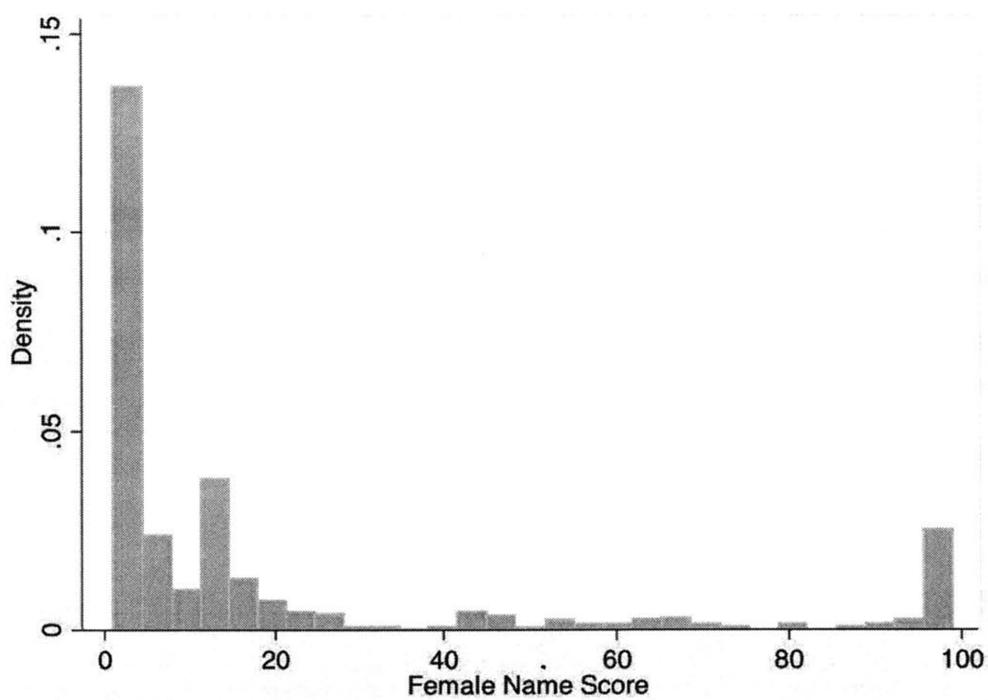

Table 1: Summary Statistics of Key Variables

Panel A: Female Name Score of less than 12					
	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
Number of Views	3,117	196.084	151.927	19.000	1,748.000
Justification Rating	2,947	3.251	0.81	0.500	5.000
Return Rating	1,025	3.463	1.054	1.000	5.000
Number of Comments	3,117	1.738	3.216	0.000	58.000
Control Variables—Recommendation-Level					
Short Position	3,117	0.160	0.367	0.000	1.000
Week-One Performance	3,117	0.007	0.080	-0.398	0.986
Expected Return	3,117	1.144	5.770	0.001	132.521
Investment Type: Growth	3,117	0.198	0.399	0.000	1.000
Investment Type: Event	3,117	0.158	0.364	0.000	1.000
Investment Type: Other	3,117	0.106	0.307	0.000	1.000
Short Investment Horizon[a]	3,117	0.407	0.491	0.000	1.000
Firm Size (B)	3,117	7.057	30.067	0.007	594.864
Control Variables—Recommender-Level[b]					
Recommendation Count	1,372	1.261	0.686	1.000	8.000
Location: Major City	1,372	0.719	0.449	0.000	1.000
Location: Non-US	1,372	0.071	0.256	0.000	1.000
Elite Undergraduate	1,372	0.340	0.474	0.000	1.000
Elite Graduate	1,372	0.321	0.467	0.000	1.000

Panel B: Female Name Score of greater than or equal to 12					
	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
Number of Views	403	173.866	128.890	1.000	1,545.000
Justification Rating	368	3.253	0.878	0.500	5.000
Return Rating	146	3.296	1.195	1.000	5.000
Number of Comments	403	1.769	4.676	0.000	74.000
Control Variables—Recommendation-Level					
Short Position	403	0.179	0.384	0.000	1.000
Week-One Performance	403	0.002	0.064	-0.450	0.247
Expected Return	403	1.059	5.809	0.003	116.275
Recommendation Type: Growth	403	0.251	0.434	0.000	1.000
Recommendation Type: Event	403	0.156	0.364	0.000	1.000
Recommendation Type: Other	403	0.109	0.312	0.000	1.000
Short Investment Horizon[a]	403	0.494	0.501	0.000	1.000
Firm Size (B)	403	7.384	22.981	0.011	275.097
Control Variables—Recommender-Level[b]					
Recommendation Count	178	1.213	0.509	1.000	4.000
Location: Major City	178	0.747	0.436	0.000	1.000
Location: Non-US	178	0.096	0.295	0.000	1.000
Elite Undergraduate[a]	178	0.416	0.494	0.000	1.000
Elite Graduate	178	0.371	0.484	0.000	1.000

Notes: This table compares summary statistics for recommenders with a *female name score* less than 12 (Panel A) to those with a *female name score* greater than or equal to 12 (Panel B). This cutoff was chosen because 12 is the lowest *female name score* observed for those who self-identified as female.
[a]For control variables: the difference between Panel A and Panel B for this variable is significantly different at $p \leq 0.05$. $\tilde{\chi}^2$ tests were used for categorical variables and t-tests were used otherwise.
[b]These data are time-invariant, therefore, only the first instance of each variable is used for each unique investment professional in the dataset.

Table 2: Correlation of Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Female Name Score	1.000													
(2) Short Position	0.020	1.000												
(3) Week-One Performance	-0.012	0.042	1.000											
(4) Expected Return	0.012	0.049	-0.021	1.000										
(5) Investment Type: Growth	0.022	-0.137	-0.018	-0.033	1.000									
(6) Investment Type: Event	-0.014	0.085	0.035	0.037	-0.219	1.000								
(7) Investment Type: Other	0.009	0.621	0.003	-0.008	-0.174	-0.149	1.000							
(8) Short Investment Horizon	0.048	0.244	0.042	-0.004	-0.043	0.232	0.134	1.000						
(9) Recommendation Count	-0.045	0.018	0.037	0.028	-0.034	0.031	-0.007	-0.007	1.000					
(10) Firm Size (B)	-0.008	-0.000	-0.014	-0.005	0.033	-0.050	0.016	-0.037	0.012	1.000				
(11) Location: Major City	0.018	0.023	0.001	-0.043	0.014	0.027	0.012	0.063	0.053	-0.013	1.000			
(12) Location: Non-US	0.014	-0.033	0.013	0.046	0.008	-0.040	-0.012	-0.022	-0.045	0.035	-0.413	1.000		
(13) Elite Undergraduate	0.057	-0.006	-0.003	-0.029	-0.013	0.040	-0.018	0.025	-0.037	-0.020	0.162	-0.133	1.000	
(14) Elite Graduate	0.054	0.047	-0.008	-0.007	-0.010	-0.033	0.026	-0.030	0.034	0.010	0.108	-0.017	0.102	1.000

Notes: Correlations greater than $|0.033|$ are significant at $p \leq 0.05$.

Table 3: Negative Binomial Regressions of Number of Views on Female Name Score

	Model 1A		Model 1B	
Female Name Score	-0.0025	***	-0.0025	***
	(0.0006)		(0.0006)	
Short Position	0.2764	***	0.2736	***
	(0.0512)		(0.0497)	
Expected Return	0.0013		0.0014	
	(0.0023)		(0.0022)	
Investment Type: Growth	-0.1568	***	-0.1556	***
	(0.0337)		(0.0334)	
Investment Type: Event	0.1780	***	0.1711	***
	(0.0387)		(0.0386)	
Investment Type: Other	-0.0174		-0.0144	
	(0.0595)		(0.0582)	
Short Investment Horizon	-0.0147		-0.0215	
	(0.0279)		(0.0282)	
Firm Size (B)	-0.0003		-0.0003	
	(0.0004)		(0.0004)	
Week-One Performance			0.3503	*
			(0.1467)	
Recommendation Count			0.0108	+
			(0.0063)	
Location: Major City			0.1091	**
			(0.0419)	
Location: Non-US			0.0523	
			(0.0627)	
Elite Undergraduate			0.0258	
			(0.0397)	
Elite Graduate			0.0009	
			(0.0364)	
Constant	4.6581	***	4.5470	***
	(0.1470)		(0.1430)	
Observations	3,520		3,520	
Log likelihood	-20,883		-20,858	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 4: Negative Binomial Regressions of Number of Views on Female Name Score—Times of Increased Search

	Model 2A		Model 2B	
Female Name Score	-0.0024	***	-0.0020	**
	(0.0006)		(0.0007)	
High Traffic	-0.1119	**	-0.0958	*
	(0.0431)		(0.0453)	
Low Traffic	0.1090	**	0.1127	**
	(0.0384)		(0.0407)	
Female Name Score X High Traffic			-0.0028	+
			(0.0016)	
Female Name Score X Low Traffic			-0.0007	
			(0.0016)	
Short Position	0.2796	***	0.2809	***
	(0.0489)		(0.0489)	
Week-One Performance	0.3622	*	0.3644	*
	(0.1453)		(0.1459)	
Expected Return	0.0016		0.0015	
	(0.0022)		(0.0022)	
Investment Type: Growth	-0.1516	***	-0.1512	***
	(0.0336)		(0.0336)	
Investment Type: Event	0.1704	***	0.1697	***
	(0.0390)		(0.0390)	
Investment Type: Other	-0.0210		-0.0226	
	(0.0566)		(0.0565)	
Short Investment Horizon	-0.0237		-0.0226	
	(0.0279)		(0.0280)	
Recommendation Count	0.0105	+	0.0105	+
	(0.0063)		(0.0062)	
Firm Size (B)	-0.0003		-0.0003	
	(0.0004)		(0.0004)	
Location: Major City	0.1112	**	0.1107	**
	(0.0421)		(0.0420)	
Location: Non-US	0.0543		0.0564	
	(0.0621)		(0.0620)	
Elite Undergraduate	0.0254		0.0240	
	(0.0393)		(0.0392)	
Elite Graduate	0.0004		0.0006	
	(0.0363)		(0.0363)	
Constant	4.4920	***	4.4880	***
	(0.1384)		(0.1382)	
Observations	3,520		3,520	
Log likelihood	-20,844		-20,842	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 5: Negative Binomial Regressions of Number of Comments on Female Name Score

	Model 3A		Model 3B	
Female Name Score	0.0013		0.0015	
	(0.0014)		(0.0013)	
Number of Views	0.0043	***	0.0043	***
	(0.0002)		(0.0002)	
Short Position	0.0971		0.0924	
	(0.0744)		(0.0750)	
Expected Return	0.0034		0.0020	
	(0.0054)		(0.0053)	
Investment Type: Growth	-0.1629	**	-0.1577	**
	(0.0590)		(0.0584)	
Investment Type: Event	0.1602	*	0.1724	**
	(0.0635)		(0.0621)	
Investment Type: Other	0.0906		0.0936	
	(0.0808)		(0.0810)	
Short Investment Horizon	-0.0403		-0.0283	
	(0.0448)		(0.0441)	
Firm Size (B)	0.0004		0.0003	
	(0.0007)		(0.0007)	
Week-One Performance			0.0488	
			(0.2370)	
Recommendation Count			-0.0022	
			(0.0072)	
Location: Major City			-0.1795	***
			(0.0542)	
Location: Non-US			0.0456	
			(0.1204)	
Elite Undergraduate			-0.1080	*
			(0.0464)	
Elite Graduate			0.0058	
			(0.0461)	
Constant	-0.3620		-0.1964	
	(0.2871)		(0.2901)	
Observations	3,520		3,520	
Log likelihood	-5,495		-5,483	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 6: OLS Regressions of Justification Rating and Return Rating on Female Name Score

	Justification Rating				Return Rating			
	Model 4A		Model 4B		Model 5A		Model 5B	
Female Name Score	0.0002		0.0001		-0.0007		-0.0008	
	(0.0010)		(0.0010)		(0.0020)		(0.0019)	
Number of Views	0.0015	***	0.0014	***	0.0013	***	0.0012	***
	(0.0001)		(0.0001)		(0.0002)		(0.0002)	
Short Position	0.0399		0.0300		-0.1489		-0.1534	
	(0.0521)		(0.0515)		(0.1153)		(0.1132)	
Expected Return	0.0006		0.0008		-0.0122		-0.0187	*
	(0.0014)		(0.0014)		(0.0091)		(0.0089)	
Investment Type: Growth	-0.1819	***	-0.1777	***	-0.2966	***	-0.2997	***
	(0.0364)		(0.0364)		(0.0889)		(0.0893)	
Investment Type: Event	0.0542		0.0535		-0.0382		-0.0397	
	(0.0435)		(0.0433)		(0.0911)		(0.0898)	
Investment Type: Other	0.0603		0.0701		0.0014		0.0267	
	(0.0599)		(0.0596)		(0.1349)		(0.1350)	
Short Investment Horizon	-0.0356		-0.0364		-0.0658		-0.0827	
	(0.0312)		(0.0310)		(0.0675)		(0.0674)	
Firm Size (B)	-0.0013	***	-0.0013	***	-0.0013	*	-0.0013	*
	(0.0004)		(0.0004)		(0.0006)		(0.0006)	
Week-One Performance			0.4865	**			1.2993	***
			(0.1709)				(0.3923)	
Recommendation Count			0.0126	*			0.0142	+
			(0.0054)				(0.0085)	
Location: Major City			0.0072				-0.0168	
			(0.0437)				(0.0800)	
Location: Non-US			-0.0178				-0.1181	
			(0.0796)				(0.1408)	
Elite Undergraduate			0.0446				0.1390	*
			(0.0352)				(0.0693)	
Elite Graduate			0.0720	*			0.0054	
			(0.0339)				(0.0684)	
Constant	3.2463	***	3.1825	***	2.6149	***	2.6079	***
	(0.2332)		(0.2298)		(0.5200)		(0.5460)	
R-Square Adj.	0.128		0.133		0.066		0.075	
Observations	3,315		3,315		1,171		1,171	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 7: Regressions of Number of Comments, Justification Rating and Return Rating on Female Name Score—Sample of Underrepresented Industries

	Number of Views[a]		Number of Comments[a]		Justification Rating[b]		Return Rating[b]	
	Model 6A		Model 6B		Model 6C		Model 6D	
Female Name Score	-0.0003		-0.0007		-0.0007		0.0025	
	(0.0011)		(0.0023)		(0.0015)		(0.0037)	
Number of Views			0.0037	***	0.0011	***	0.0004	
			(0.0004)		(0.0002)		(0.0004)	
Short Position	0.1420		-0.0180		-0.2974	*	-0.7138	*
	(0.1266)		(0.1955)		(0.1356)		(0.3126)	
Week-One Performance	0.4593		-0.5553		0.3552		-0.6311	
	(0.4280)		(0.6046)		(0.3844)		(1.3080)	
Expected Return	0.0365		0.0370		0.0467	*	-0.0360	
	(0.0387)		(0.0248)		(0.0218)		(0.1061)	
Investment Type: Growth	-0.2367	**	-0.3390	*	-0.1565		-0.8484	**
	(0.0826)		(0.1416)		(0.1027)		(0.2867)	
Investment Type: Event	0.2460	**	0.2342	+	0.2502	*	0.0989	
	(0.0890)		(0.1397)		(0.0971)		(0.2239)	
Investment Type: Other	0.0697		0.3856	+	0.2447		0.3991	
	(0.1400)		(0.2168)		(0.1637)		(0.4072)	
Short Investment Horizon	0.0399		-0.1246		-0.0169		-0.2609	
	(0.0628)		(0.1033)		(0.0786)		(0.1923)	
Recommendation Count	-0.0042		-0.0123		0.0082		-0.0114	
	(0.0092)		(0.0190)		(0.0118)		(0.0166)	
Firm Size (B)	-0.0050	***	-0.0019		-0.0044		-0.0042	
	(0.0011)		(0.0035)		(0.0030)		(0.0030)	
Location: Major City	0.1201	+	-0.1121		-0.0979		0.0622	
	(0.0647)		(0.1327)		(0.0977)		(0.2461)	
Location: Non-US	0.1465		-0.1922		-0.1125		-0.1710	
	(0.1289)		(0.2027)		(0.2190)		(0.3833)	
Elite Undergraduate	-0.0669		-0.0789		0.1876	**	0.3572	+
	(0.0629)		(0.1006)		(0.0701)		(0.2108)	
Elite Graduate	-0.0205		0.1229		0.0017		-0.1046	
	(0.0568)		(0.1042)		(0.0739)		(0.2062)	
Constant	4.4638	***	-0.4119		3.3781	***	4.0548	***
	(0.1690)		(0.3313)		(0.2501)		(1.0813)	
R-Square Adj.					0.148		0.187	
Observations	490		490		461		152	
Log likelihood	-2,912		-780					

Notes: Unit of analysis is the investment recommendation. Underrepresented industries were defined as those with a below the median number of recommendations. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

[a]Negative binomial regression

[b]OLS regression

Table 8: Negative Binomial Regressions of Number of Views on Female Name Score—Recommenders Who Self-Identified as Male

	Model 7A	
Female Name Score	-0.0027	**
	(0.0010)	
Short Position	0.2344	***
	(0.0627)	
Week-One Performance	0.4513	*
	(0.1780)	
Expected Return	0.0023	
	(0.0037)	
Investment Type: Growth	-0.2052	***
	(0.0451)	
Investment Type: Event	0.1225	**
	(0.0466)	
Investment Type: Other	-0.0521	
	(0.0812)	
Short Investment Horizon	0.0072	
	(0.0427)	
Recommendation Count	0.0130	*
	(0.0066)	
Firm Size (B)	-0.0003	
	(0.0004)	
Location: Major City	0.1178	*
	(0.0541)	
Location: Non-US	0.1037	
	(0.0742)	
Elite Undergraduate	0.0189	
	(0.0556)	
Elite Graduate	0.0383	
	(0.0492)	
Constant	4.8701	***
	(0.1029)	
Observations	1,637	
Log likelihood	-9,660	

Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects with robust standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table 9: Regressions of Evaluation Process on Female Name Score—Census Matched First Names

	Views[a]		Comments[a]		Justification Rating[b]		Return Rating[b]	
	Model A1		Model A2		Model A3		Model A4	
Female Name Score	-0.0024	***	0.0022		0.0000		-0.0018	
	(0.0007)		(0.0015)		(0.0011)		(0.0022)	
Number of Views			0.0042	***	0.0014	***	0.0012	***
			(0.0003)		(0.0002)		(0.0002)	
Short Position	0.3015	***	0.0708		0.0281		-0.2484	+
	(0.0590)		(0.0861)		(0.0591)		(0.1298)	
Week-One Performance	0.3445	*	0.1047		0.4825	**	1.0898	**
	(0.1655)		(0.2638)		(0.1860)		(0.4106)	
Expected Return	0.0010		0.0036		0.0026	*	-0.0374	
	(0.0029)		(0.0052)		(0.0012)		(0.0426)	
Investment Type: Growth	-0.1765	***	-0.1283	*	-0.1705	***	-0.2884	**
	(0.0365)		(0.0643)		(0.0408)		(0.1005)	
Investment Type: Event	0.1746	***	0.1723	**	0.0600		0.0301	
	(0.0434)		(0.0663)		(0.0483)		(0.1045)	
Investment Type: Other	-0.0419		0.1500		0.0967		0.1463	
	(0.0686)		(0.0927)		(0.0674)		(0.1542)	
Short Investment Horizon	-0.0006		0.0011		-0.0544		-0.1246	+
	(0.0318)		(0.0497)		(0.0345)		(0.0754)	
Recommendation Count	0.0119	+	-0.0027		0.0099	+	0.0131	
	(0.0066)		(0.0078)		(0.0057)		(0.0090)	
Firm Size (B)	-0.0001		-0.0000		-0.0010	**	-0.0011	+
	(0.0004)		(0.0008)		(0.0004)		(0.0006)	
Location: Major City	0.1007	*	-0.1779	**	0.0100		-0.0230	
	(0.0458)		(0.0589)		(0.0463)		(0.0914)	
Location: Non-US	0.0467		0.1630		-0.0017		-0.0999	
	(0.0791)		(0.1557)		(0.1014)		(0.1848)	
Elite Undergraduate	0.0461		-0.0924	+	0.0476		0.1700	*
	(0.0452)		(0.0527)		(0.0395)		(0.0749)	
Elite Graduate	-0.0087		0.0038		0.0734	+	0.0175	
	(0.0395)		(0.0524)		(0.0383)		(0.0747)	
Constant	4.5388	***	-0.0421		3.3878	***	2.3988	***
	(0.1584)		(0.2770)		(0.1763)		(0.6393)	
R-Square Adj.					0.131		0.081	
Observations	2,828		2,828		2,667		919	
Log likelihood	-16,753		-4,374					

Notes: Notes: Unit of analysis is the investment recommendation. Models contain year and industry fixed effects. Robust Standard errors, clustered at the recommender-level, in parentheses. Significance levels: + $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
[a]Negative binomial regression
[b]OLS regression

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