London School of Economics and Political Science

Essays on information asymmetry and financial institutions

Nelson Camanho da Costa Neto

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Abstract

The thesis consists of three chapters that investigate informational asymmetry mechanisms surrounding financial institutions.

In the first chapter, my co-authors and I develop a theoretical model to analyse the effect of competition on the conflict of interest arising from the issuer pay compensation model of the credit rating industry. We find that relative to monopoly, rating agencies are more likely to inflate ratings under competition, resulting in lower expected welfare. These results do not depend on the presence of ratings shopping, but instead focus on the trade-off between maintaining reputation (to increase profits in the future) and inflating ratings today (to increase current profits).

In the second chapter, I document a direct link between stock mispricing, as proxied by mutual fund flow-driven price pressure, and corporate investment. One standard deviation increase in stock price pressure leads to an increase of 1.3 percent in investment. High price pressure firms with high investments have lower future stock returns and lower future operational performance than high price pressure firms with low investments. Investment sensitivity to price pressure is stronger for firms that are less financially constrained, firms with high churn rates (shorter horizon) and firms with high R&D intensity (with more opaque assets). Finally, investment sensitivity to price pressure remains positive and significant for firms that do not engage in seasoned equity offerings around the investment period, suggesting there is a channel between stock price pressure and corporate investment that is independent of external financing.

The third chapter documents a pronounced market timing ability of institutional investors when it comes to selling individual stocks. Based on more than 8 million institutional trades over the period 1999 to 2009, my co-authors and I document that (i) large (block) sales of institutional investors correlate with future negative excess returns, while stock purchases do not predict positive excess returns at the stock level, (ii) the one-sided successful market timing of block liquidations is more pronounced if the block represents a larger share of the investor portfolio or/and the stock capitalization, (iii) international investors have a weaker one-sided timing ability for block liquidations. The evidence strongly supports the hypothesis that proximity of block holding investors to management provides important inside information advantages.

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Contents

List of Figures

List of Tables

Chapter 1

Credit Rating and Competition

Co-authored with Zijun Liu (London School of Economics) and Pragyan Deb (London School of Economics)

1.1 Introduction

The credit rating industry aims to offer investors valuable information about issuers in need of financing. Due to the asymmetric information between the issuers and the investors, credit ratings often have pivotal impacts on the issuers' financing outcomes. Before the 1970s, the rating agencies relied on an investor-pay model wherein investors subscribed to ratings released by the agencies and these subscription revenues were the main source of income for the rating agencies. However owing to the 'public good' nature of ratings[1] and the increase in free riding, rating agencies switched to the current issuer-pay model and started charging issuers for ratings. As things stand today, the largest source of income for the rating agencies[2] are the fees paid by the issuers the rating agencies are supposed to impartially rate.[3] This tempts rating agencies to rate better than what fundamentals suggest.

[1]This was officially recognized by the Securities and Exchange Commission (SEC) in the 1970s when the big three rating agencies – Standard & Poor's, Moody's and Fitch were designated self-regulatory entities. See Lowenstein (2008).

[2]It is also interesting to note that rating agencies are some of the most profitable businesses. Moody's was the third most profitable company in the S&P 500-stock index from 2002 to 2007, based on pretax margins (ahead of both Microsoft and Google).

[3]Summary Report of Issues Identified in the Commission Staff's Examinations of Select Credit Rating Agencies by the Staff of the Securities and Exchange Commission, 2008, p.9.

Such behavior has been criticized heavily since the onset of the recent financial crisis, in particularly over the AAA ratings that have been issued to complex structured products. Rating agencies played a crucial role in the rapid growth of structured finance. According to Fitch Ratings (2007), around 60% of all global structured products were AAA-rated, compared to less than 1% for corporate and financial issues. Following a subsequent jump in default rates, rating agencies lowered the credit ratings on structured products widely, indicating that the initial ratings were likely inaccurate.

A number of empirical papers find that the conflicts of interest problem play an important role in rating agencies' decisions. Griffin and Tang (2011) give striking empirical evidence of ratings inflation by rating agencies. They compare the CDO assumptions made by the ratings department and by the surveillance department within the same rating agency, and find the former uses more favorable assumptions. Moreover, it appears that the signals from the surveillance department were ignored and the CDOs favored by the ratings department were subsequently downgraded. Xia and Strobl (2012) provide further evidence of ratings inflation as a result of the issuer-pay model. They compare the ratings issued by Standard & Poor's Ratings Services (S&P) which follows the issuer-pay model to those issued by the Egan-Jones Rating Company (EJR) which adopts the investor-pay model. They find that S&P inflates more relatively to EJR when S&P's conflict of interest is more acute.

It is often suggested that introducing more competition between rating agencies may help alleviate the conflicts of interest problem. However, a growing body of academic literature suggests that this may not be the case. Skreta and Veldkamp (2009) show that, in the presence of asset complexity and ratings shopping, competition leads to lower welfare in equilibrium. Bolton, Freixas and Shapiro (2012) also find that competition leads to more ratings inflation as issuers are able to more easily shop for ratings and that this effect is particular acute in boom times, when investors are more trusting. The contribution of our paper is to show that even in the absence of ratings shopping and asset complexity, and with rational investors, competition delivers lower welfare than monopoly. Our results stem from the fact that enhanced competition in the form of a new entrant reduces the incumbent's market share for ratings. This market sharing effect reduces the rent that rating agencies can derive from maintaining their reputation, encouraging ratings inflation even in the absence of ratings shopping. Our results suggest that current regulatory attempts to reduce ratings shopping[4] may not eliminate ratings inflation due to the underlying conflicts of interest problem.

We develop an infinite horizon model where rating agencies compete for market share and face a trade-off between reputation and current fees. Competition in our model has two effects - the disciplining effect and the market-sharing effect. Competition decreases ratings inflation through the disciplining effect as rating agencies have incentives to maintain or gain the market leadership. This channel is generally emphasized when it is argued that enhanced competition between rating agencies can resolve the conflict of interest. However, this ignores the other effect of competition - the reward from maintaining reputation is lower because competition implies that the market is shared between a larger number of rating agencies. We call this the market-sharing effect and study the impact of competition on the behavior of rating agencies by exploring the interaction between these two opposite effects. Our results suggest that on balance the latter effect dominates and higher competition results in greater ratings inflation.

Given the structure of the market - with S&P's and Moody's having 80% of market share,[5] we model competition amongst the rating agencies in a duopolistic setting. In our model, issuers need a good rating to finance their projects. Rating agencies,

[4]See Sangiorgi and Spatt (2011). Note that in a rational expectations setting, ratings inflation might arise due to the possibility of unpublished ratings, which might be countered by regulation.

[5]The figure stands at 95% if we include the third major player, Fitch.

which can be of two types - *honest* or *strategic*, perfectly observe the quality of the project and can either give the issuer a good rating or refuse rating. An honest rating agency always gives good ratings to good projects and no rating to bad projects while a strategic rating agency acts to maximize its expected profits. Neither investors nor issuers know for sure if a rating agency is honest and they Bayesian update on the reputation of the rating agencies, *i.e.* the probability that a rating agency is honest. The market share of the rating agency is modeled such that rating agencies with higher reputation attract more projects. Hence the rating agencies face a trade-off between current income and reputation which determines their future market share and income.

We compare the behavior of rating agencies between the monopolistic case and a simultaneous[6] duopolistic case.[7] We first derive closed-form solutions in a three-period model and show that the lax behavior of a rating agency increases with the reputation of its competitor, *i.e.* competition leads to more lax behavior and the market-sharing effect dominates. We then compute numerical solutions under an infinite-period setting, which enables us to relax parameter restrictions and extend the horizon of rating agencies, thereby making reputation more important for them.

Our results show that the market-sharing effect tends to dominate the disciplining effect when the degree of competition is sufficiently high, *i.e.* the reputation of the competitor is high. Moreover, we find that expected welfare is higher in the monopoly case than in the duopoly case as long as the reputation of the entrant rating agency (the competitor) is not greater than that of the incumbent rating agency. In our model, expected welfare rises only when the new entrant has a higher reputation vis-à-vis the incumbent, a situation which appears unlikely. We verify that the results

[6]There is no incentive for herding as this is not a sequential model: rating agencies are either monopolists or have one competitor with known reputation.

[7]Although we only focus on competition in a duopolistic setting, our results intuitively extend to situations with higher degrees of competition.

are robust to different parameter specifications and on balance, our results suggest that increasing competition is likely to result in more ratings inflation.

The rest of the paper is organized as follows. Section 1.2 reviews the literature. In Section 1.3 we outline the basic features of our model. Section 1.4 describes the equilibrium in our model and Section 1.5 solves the model solution in a three-period setting. In Section 1.6 we solve the model numerically in an infinite horizon. We go on to compare the behavior of rating agencies under monopoly and duopoly and discuss the expected welfare consequences of enhanced competition. Section 1.7 concludes. The proofs and additional robustness checks are presented in the Appendix.

1.2 Literature Review

Mathis, McAndrews and Rochet (2009) demonstrate that reputational concerns are not enough to solve the conflict of interest problem. In equilibrium, rating agencies are likely to behave laxly, *i.e.* rate bad projects as good and are prone to reputation cycles. Our model innovates by introducing competition through an endogenous market share function and studying how competition affects the behavior of rating agencies.

Becker and Milbourn (2011) lends support to our results by providing an empirical test of the impact of competition on rating agencies. They measure competition using the growth of Fitch's market share and find three pieces of evidence. First, the overall standards of ratings issued by S&P and Moody's increased (closer to the top AAA rating) with competition, so that ratings became more 'friendly'. Second, the correlation between bond yields and ratings fell as competition increased, implying that ratings became less informative. Third, equity prices started reacting more negatively to rating downgrades, suggesting a lower bar for rating categories. Their findings are consistent with our results that competition will tend to lower the quality of ratings in the market.

A recent paper by Xia (2012) provides some contrasting empirical evidence. The author compares S&P's rating quality before and after the entry of an investor paid rating agency and finds a significant improvement in the quality of S&P's ratings following the entry of the new rating agency. This result however is completely compatible with our model since an investor paid rating agency in our setting would be perfectly honest and our results suggest that in cases in which the incumbent RA has lower reputation than the entrant RA, welfare improvement is possible.

There has been an extensive literature that studies competition through reputation. For example, Horner (2002) shows that the incentive to maintain good reputation and stay in the market can induce good firms to exert higher effort and try to distinguish themselves from the bad ones. The adverse effects of competition on the building and maintenance of reputation has been studied by Klein and Leffler (1981). They argue that when faced with a choice between supplying high quality products or low quality ones, firms would be induced to supply high quality products only when the expected value of future income given a high reputation outweighs the short-run gain of lying. Bar-Isaac (2003) points out that the overall effect of competition on reputational incentives is ambiguous and may be non-monotonic, since increased competition can reduce the discounted value of maintaining a high reputation on the one hand, but can also lead to a more severe punishment for low reputation on the other. This intuition is very close to ours, except that we use a richer framework in the context of credit rating agencies.

Bouvard and Levy (2009) examine the trade-off between reputation and profits of rating agencies in a competitive setting and find that the threat of entry attenuates reputational effects. Mariano (2012) models how reputational concerns change rating agencies incentives to reveal private information. In a setting in which rating agencies have access to private and public information, her results provide a mechanism in which competition between rating agencies might inflate the ratings even in the absence of conflicts of interest. Compared to the above, the innovation of our paper is to endogenize the market share of rating agencies and to explore the welfare implications of competition.

Damiano, Hao and Suen (2008) study how the rating scheme may affect the strategic behavior of rating agencies. They compare ratings inflation among centralized (all firms are rated together) and decentralized (firms are rated separately) rating schemes. When the quality of projects is weakly correlated, centralized rating dominates because decentralized rating leads to lower ratings inflation. The reverse holds when the correlation is strong. Sangiorgi, Sokobin and Chester (2009) model and analyze the equilibrium structure of ratings reflected by ratings shopping. They interpret how the correlation between different rating agencies' models influence ratings shopping and bias. They also use selection as an equilibrium interpretation for notching by a rival rating agency. Moreover, they show that a higher cost of obtaining indicative ratings lead to inflation in published ratings, as they are obtained less frequently.

Ashcraft, Goldsmith-Pinkham and Vickery (2010) study credit ratings on subprime and Alt-A mortgage-backed-securities (MBS) deals issued between 2001 and 2007. Although they find that the fraction of highly rated securities in each deal is decreasing in mortgage credit risk, their results suggest a progressive decline in standards around the MBS market peak between the start of 2005 and mid-2007.

White (2010) gives a historic overview of the market of the credit rating agencies and suggest that the regulatory framework contributed to the subprime mortgage debacle and associated financial crisis. They highlight how the major reliance of regulators on major rating agencies propelled them to the center of US bond markets and led the mistakes by those rating agencies to have serious consequences for the financial sector.

Bar-Isaac and Shapiro (2011) explore how the labor market for analysts and their incentives influence ratings accuracy. Motivated by the fact that rating analysts were fleeing the rating agencies for better paid investment bank jobs, they build a 2 period model in which analysts work for rating agencies in period 1 and can leave them to a better paid investment bank in period 2. They show that ratings accuracy increases with monitoring and also with investment bank profitability (as analysts train harder in period 1), but it is non-monotonic in the probability of the analyst getting a job in the investment bank.

Bar-Isaac and Shapiro (2012) analyze how reputational concerns of rating agencies vary over the business cycle. A rating agency is more likely to issue less-accurate ratings in boom times, when income from fees is high, competition in the labor market for analysts is tough, and default probabilities for the securities rated are low. They also show that competition among the rating agencies delivers similar qualitative results. However, competition is not the main focus of their paper and is modeled through an exogenous function between the degree of competition and the fees received by rating agencies.

1.3 Model Setup

We consider a discrete time setting with 3 types of agents – the issuers, the rating agencies (RA) and the investors. Each period, we have a *new issuer*[8] with a project that requires financing. We assume that issuers do not have funds of their own and need to obtain outside financing. The investors have funds and are willing to invest in the project provided they are convinced that it is profitable to do so. The role of the RA in this setting is to issue ratings that convince investors to provide financing.

More formally, each period we have one issuer that has a project which lasts for one period. All projects have a fixed pay-off Φ if successful and 0 otherwise and require

[8] *New Issuer* implies that it is a one shot game for the issuer and we rule out the possibility that issuers try to maximize profits over multiple periods. This assumption also ensures that issuers have the same belief as the investors about the reputation of the RAs. If we allow the same issuers to approach the rating agencies in subsequent periods, then issuers will have more information than investors.

an investment of X. This required investment X is uniformly distributed over (a,b) and its realization is observed by all agents. The uniform distribution assumption ensures that we have a range of projects with different returns. Projects that require low investment have high return and vice versa. We can get similar results if we assume fixed investment with uncertain pay-off. The project is *good* with probability λ and *bad* with probability $1-\lambda$, and λ is independent of X. Good projects succeed with probability p_G and fail with probability $(1-p_G)$. Bad projects always fail.

We assume that *a-priori* projects are not worth financing without rating, *i.e.* $\lambda p_G \Phi \leq X$. Further, the RAs can perfectly observe the type of project at no cost. After observing the type, the RA can either issue a good rating (GR) or no rating (NR). Note that we do not distinguish between bad rating and NR and abstract away from a ratings scale. In our setup, a good rating is one that allows the issuer to borrow from investors. It does not matter if this rating is AAA or A or BBB or even C. As long as the rating allows the firm to get financing, we consider it to be a GR. A bad rating in this setting will be a rating which does not enable a project to get financing. This is the same outcome as a NR and thus, a bad rating and NR are equivalent in our model.

The rating agency receives income I if it issues GR, and 0 otherwise.[9] This assumption arises from the conflict of interest in the ratings industry. Given the *non-transparent* nature of the market and the widespread use of *negotiated ratings*, issuers and RAs routinely have negotiations and consultations before an official rating is issued. RAs, as part of their day-to-day operations, give their clients 'creative suggestions' on how to repackage their portfolios or projects in order to get better ratings. To quote former chief of Moody's, Tom McGuire[10]

"The banks pay only if [the rating agency] delivers the desired rating…

[9]This is a standard simplifying assumption in the literature. See Mathis et al. (2009) and Skreta and Veldkamp (2009).

[10]New York Times Magazine, Triple-A-Failure, April 27, 2008.

If Moody's and a client bank don't see eye-to-eye, the bank can either tweak the numbers or try its luck with a competitor..."

We assume that there are two types of RAs - *honest* and *strategic* . An honest RA always issues a GR to a good project and NR to a bad project while a strategic RA behaves strategically to maximize its expected future profits. The strategic RA faces the following trade-off :

1. (**Truthful**) It can either be truthful and maintain its reputation, thus ensuring profits in the future

2. (**Lie**) It can inflate ratings (give a good rating to a bad project) and get fees now, at the cost of future profits

We consider a duopolistic setting of rating agencies.[11] The type of the RA is chosen *ex ante* by nature and is known only to the rating agency itself. The *reputation* of the rating agency is defined as the probability that it is honest, denoted by $q_i, i \in \{1, 2\}$. The reputation evolves over time depending on the ratings and outcome of the projects. The *strategy* of the RA is x_i, the probability the RA issues a GR to a bad project.[12]

The investors (and issuers) have some priors about the types of the RAs and they Bayesian update on their beliefs. Firstly, investors and issuers take into account the rating and update the reputation of the RA, before observing the outcome of the project. Given prior reputation q_t,

$$\text{If RA issues GR, } q_t^{GR} = \frac{\lambda q_t}{\lambda + (1 - q_t)(1 - \lambda)x} < q_t \tag{1.1}$$

$$\text{If not rated, } q_{t+1}^{N} = \frac{q_t}{1 - x(1 - q_t)} > q_t \tag{1.2}$$

[11]Given the structure of the market, with Moody's and S&P controlling nearly 80% of the market, we believe that this is a reasonable approximation of reality.

[12]Note that in equilibrium the strategic RA will always issue GR to a good project (see Section 1.4).

If the project is issued a good rating by the RA, the investors update their beliefs after observing the outcome of the project.

$$\text{If the project succeeds, } q^S_{t+1} = \frac{\lambda p_G q_t}{\lambda p_G q_t + \lambda p_G (1-q_t)} = q_t \tag{1.3}$$

$$\text{If the project fails, } q^F_{t+1} = \frac{\lambda(1-p_G)q_t}{\lambda(1-p_G)q_t + [\lambda(1-p_G) + (1-\lambda)x](1-q_t)} < q_t \tag{1.4}$$

We make the simplifying assumption that each issuer can only approach one RA for rating. Therefore, our model considers ratings shopping only to the extent that the issuer and the rating agency have negotiations before an official rating is issued. We do not explicitly study multiple ratings and herd behavior of the RAs. While these are important issues that merit attention, they are not the focus of this paper. Here we look at the competition for market share among rating agencies and show that ratings inflation increases with competition.

Investors observe the rating decision and decide whether to invest. If they observe a GR from a RA with reputation q, their subjective belief that the project will succeed (using equation (1.1)) is given by

$$\begin{aligned} s(q,x) &= q^{GR} p_G + (1-q^{GR})\frac{\lambda p_G}{\lambda + (1-\lambda)x} \\ &= \frac{\lambda q}{\lambda + (1-q)(1-\lambda)x} p_G + \left(1 - \frac{\lambda q}{\lambda + (1-q)(1-\lambda)x}\right)\frac{\lambda p_G}{\lambda + (1-\lambda)x} \\ &= \frac{\lambda p_G}{\lambda + (1-q)(1-\lambda)x} \end{aligned} \tag{1.5}$$

Given the required investment level X, investors are willing to finance the project *if and only if* $X \leq s(q,x)\Phi$, *i.e.* if the initial investment required for the project is no greater than its expected pay-off. Without loss of generality, assume $s(q_1, x_1) > s(q_2, x_2)$. We have 3 cases:

1. If X is such that a good rating from either RA is enough, *i.e* $X \leq s(q,x)\Phi$ for both q_1 and q_2, the firm can approach either RA.[13] We assume that in this case

[13] We assume that the issuers are only paid when projects succeed. This implies that the issuers will be indifferent between RAs (with different reputation) given that both can guarantee financing.

the firm will randomly choose one of the RAs, *i.e.* the project goes to both RAs with equal probability.[14]

2. If $s(q_2, x_2)\Phi < X < s(q_1, x_1)\Phi$, *i.e.* only the high reputation RA can issue ratings that can convince the investors to provide financing, hence the firm will go to RA1 and not RA2.

3. If $X > s(q_1, x_1)\Phi$, the project does not get financed.

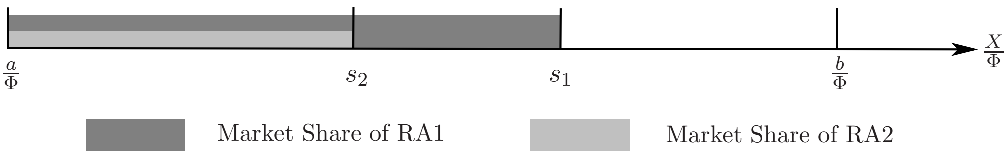


Figure 1.1: The Market for Ratings

Thus we get the following result as illustrated in Figure 1.1 -

$$\text{Probability that a project comes to RA1} = \frac{(s_1 - s_2) + \frac{1}{2}\left(s_2 - \frac{a}{\Phi}\right)}{\frac{b}{\Phi} - \frac{a}{\Phi}}$$

$$\text{Probability that a project comes to RA2} = \frac{\frac{1}{2}\left(s_2 - \frac{a}{\Phi}\right)}{\frac{b}{\Phi} - \frac{a}{\Phi}}$$

We set $(a, b) = (\lambda p_G \Phi, p_G \Phi)$, because any project with $X < \lambda p_G \Phi$ does not need a rating to be financed, and any project with $X > p_G \Phi$ is never worth financing *ex-ante*.

$$\text{The probability that a project comes to RA1} = \frac{s_1 - \frac{1}{2}\left(s_2 + \lambda p_G\right)}{p_G(1 - \lambda)} \tag{1.6}$$

$$\text{The probability that a project comes to RA2} = \frac{\frac{1}{2}\left(s_2 - \lambda p_G\right)}{p_G(1 - \lambda)} \tag{1.7}$$

Reputation plays a critical role in our model. The market share of the RAs depends on s, and thus on reputation q. Since the income from giving a GR is constant (denoted by I), the future profits of the RA will solely depend on its market share.

[14]Note that this is one of infinite many possible equilibria. Since the issuers are indifferent, we have an equilibrium for all probabilities ($\alpha \in (0, 1)$) of approaching a specific RA . We focus on the case where $\alpha = \frac{1}{2}$. Our qualitative results do not depend on the choice of α.

Moreover, the RA with a higher reputation enjoys additional benefits of being the market leader, because it owns entirely the proportion of the market that cannot be rated by its competitor but can be rated by itself, whereas its competitor can only share its market with the leader. This creates incentives for RAs to maintain or gain the market leader position and hence disciplines the RAs through competition.

We can now see that competition (modeled through market share) has two effects on lax behavior: the market-sharing effect and the disciplining effect. The market-sharing effect refers to the fact that the RA finds lying and receiving income today more attractive as its expected future income is shared with another RA, and the disciplining effect refers to the fact that the RA finds lying less attractive in order to maintain/gain the advantages of being a market leader. We will show later that the market-sharing effect tends to dominate the disciplining effect and hence competition aggravates the lax behavior of RAs in general.

1.4 Equilibrium

Definition 1. *The equilibrium in our model is a Markov Perfect Equilibrium such that, at each period t, the strategic RA always*

(i) Gives a good rating to a good project.

(ii) Gives a good rating to a bad project with probability x_t, where $0 \leq x_t \leq 1$.

We look for a Markov Perfect Equilibrium in the sense that the equilibrium is “memoryless", *i.e.* the strategy of the strategic RA only depends on the current reputation of its opponent and itself. The equilibrium is also “symmetric", as the strategy function of both RAs (if they are both strategic) is the same. However, the RAs do not take actions simultaneously.

Let RA1 be a strategic RA and let $V_t(q_1, q_2)$ denote its discounted future profits, given its reputation q_1 and its competitor's reputation q_2, and let δ be the discount

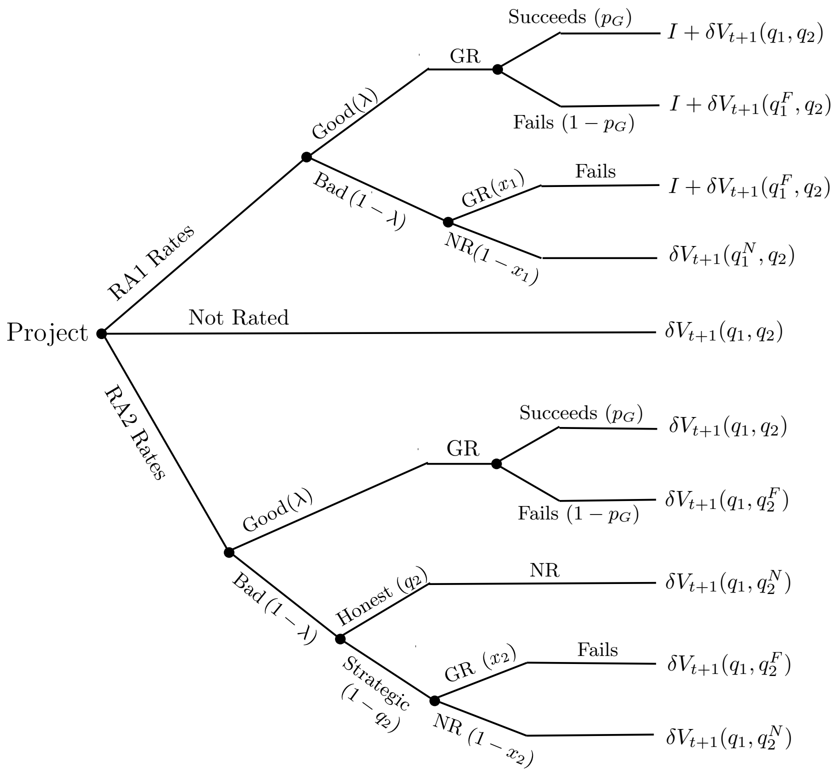


Figure 1.2: Decision-tree for Strategic RA1

rate. The RA's new reputation after it gives NR and the failure of a project following a GR are denoted by q_1^N and q_1^F respectively. A successful project with a GR leaves the RA's reputation unchanged. Note that q_1^F and q_1^N are functions of the strategy of the RA and its current reputation level. For notational simplicity, we suppress the time subscript of these reputation-updating functions.

Figure 1.2 shows the decision tree of RA1. Suppose it is approached for rating. If the project is good, RA1 gives it a GR and gets income I (see Proposition 2 below). On the other hand, if the project is bad, RA1 strategically decides whether to give a GR and get fees I or refuse rating. In case of NR, RA1's reputation rises as it gets a larger market share in the future. In case of a GR, RA1's reputation falls if the project fails and remains the same if it succeeds. This in turn determines the RA1's expected future income. A similar analysis applies if RA2 is approached for rating. In this case the fees go to RA2 and RA1 is only indirectly affected through a change in RA2's reputation. Note that since RA1 does not know the type of RA2, it has to take into account the possibility that RA2 is either honest or strategic.

$$
\begin{aligned}
V_t(q_1,q_2) = P(RA1rates)\Big\{ & P(Good)\big[I + p_G\delta V_{t+1}(q_1,q_2) + (1-p_G)\delta V_{t+1}(q_1^F,q_2)\big] \\
& + P(Bad)\big[x_1(q_1,q_2)\big(I+\delta V_{t+1}(q_1^F,q_2)\big) + \big(1-x_1(q_1,q_2)\big)\delta V_{t+1}(q_1^N,q_2)\big]\Big\} \\
& + P(RA2rates)\Big\{ P(Good)\big[p_G\delta V_{t+1}(q_1,q_2) + (1-p_G)\delta V_{t+1}(q_1,q_2^F)\big] \\
& + P(Bad)\Big[(1-q_2)x_2(q_1,q_2)\delta V(q_1,q_2^F) + \big[q_2 + \big(1-q_2\big)\big(1-x_2(q_1,q_2)\big)\big]\delta V(q_1,q_2^N)\Big]\Big\} \\
& + P(NotRated)\delta V_{t+1}(q_1,q_2) \qquad (1.8)
\end{aligned}
$$

The objective function of RA1 is to maximize $V_t(q_1,q_2)$, the strategy being x_1. Note that RA1's strategy is only effectual when it rates a bad project. In all other cases, RA1's strategy is inconsequential.

Proposition 1. *There exists a unique x_1, where $0 \leq x_1 \leq 1$, given that $V_t(q_1,q_2)$ is an increasing function in q_1.*

Proof. See Appendix 1.8.1 □

Intuitively, it is easy to see from equation (1.8) that $V_t(q_1,q_2)$ is linear in x_1. This ensures that RA1's maximization problem has a unique solution.

Proposition 2. *A strategic RA does not have incentives to give NR to a good project.*

Proof. See Appendix 1.8.1 □

Proposition 2 implies that a strategic RA always gives GR to a good project. This is because it gets a lower pay-off if it deviates from this strategy and gives a NR to a good project. The proposition follows directly from the pay-off structure of the RAs and the beliefs.

Proposition 3. *There exists a unique equilibrium as described in Definition 1.4.*

Proof. Follows from Propositions 1 and 2. □

Corollary 1. *Assume $p_G < 1$. Then the equilibrium strategy of the strategic RA is always positive, i.e. it inflates ratings with positive probability.*

Proof. See Appendix 1.8.1 □

Corollary 2. *Suppose the model ends in period T. Then the equilibrium strategy of the strategic RA is $x = 1$ at $t = T-1, T$.*

Proof. See Appendix 1.8.1 □

We now present an analytical solution in a finite period setting. We solve the model numerically in infinite horizon in Section 1.6.

1.5 Finite Horizon Solution

We assume the model lasts for three periods, $t = 1, 2, 3$, and the RAs maximize their expected total income over the three periods. We compute the equilibrium strategy of the RAs using backward induction. We already know that the strategic RA will always lie in the last two periods, as shown in Corollary 2.

We solve for the equilibrium strategy at $t = 1$. Again, let's look at the decision of RA1. Since RA1 will always lie at $t = 2, 3$, the expected pay-off of RA1 at $t = 1$ is

$$
\begin{aligned}
\Psi(lie) = I + \delta V_2(q_1^F, q_2) = I + \delta f(q_1^F, 1, q_2, 1)I \\
+ \delta^2 \Big\{ f(q_1^F, 1, q_2, 1)[\lambda p_G f(q_1^F, 1, q_2, 1) + ((1-p_G)\lambda + (1-\lambda)) f(q_1^{FF}, 1, q_2, 1)] \\
+ f(q_2, 1, q_1^F, 1)[\lambda p_G f(q_1^F, 1, q_2, 1) + \big(\lambda(1-p_G) + (1-\lambda)(1-q_2)\big) f(q_1^F, 1, q_2^F, 1) \\
+ (1-\lambda) q_2 f(q_1^F, 1, q_2^N, 1)] \Big\} I
\end{aligned}
\tag{1.9}
$$

if it lies, and

$$
\begin{aligned}
\Psi(honest) = \delta V_2(q_1^N, q_2) = \delta f(q_1^N, 1, q_2, 1)I \\
+ \delta^2 \Big\{ f(q_1^N, 1, q_2, 1)[\lambda p_G f(q_1^N, 1, q_2, 1) + ((1-p_G)\lambda + (1-\lambda)) f(q_1^{NF}, 1, q_2, 1)] \\
+ f(q_2, 1, q_1^N, 1)[\lambda p_G f(q_1^N, 1, q_2, 1) + \big(\lambda(1-p_G) + (1-\lambda)(1-q_2)\big) f(q_1^N, 1, q_2^F, 1) \\
+ (1-\lambda) q_2 f(q_1^N, 1, q_2^N, 1)] \Big\} I \qquad (1.10)
\end{aligned}
$$

if it is honest, where $f(q_1, x_1, q_2, x_2)$ is the probability that the project comes to RA1 next period, given its reputation q_1, its strategy x_1, its competitor's reputation q_2 and its competitor's strategy x_2.

As described in Section 1.4, we look for an equilibrium of the game by examining the trade-off facing RA1, *i.e.* the difference between expressions (1.9) and (1.10). If the pay-off from lying is greater then $x_1 = 1$ and we have a pure-strategy equilibrium in which RA1 always lies; if the pay-off from not lying is greater then $x_1 = 0$ and we have a pure-strategy equilibrium in which RA1 never lies; otherwise we have a mixed-strategy equilibrium in which RA1 is indifferent between lying and not lying, given some prior beliefs about its strategy, *i.e.* $0 < x_1 < 1$.

To derive an analytical solution to this game, we make a simplifying assumption that $p_G = 1$ and $\delta = 1$. This assumption implies that the reputation of the strategic RA goes to zero if it gives a GR to a bad project since now every good project succeeds and every bad project fails. This simplifies expressions (1.9) and (1.10) and allows us to derive the equilibrium strategy of RA1. This assumption is relaxed in Section 1.6.

The expression of market share of RA1 depends on whether RA1 has a higher probability of success than its competitor. Given that the strategy of the strategic RA in the last two periods is to always lie, the RA with a higher reputation will have a higher market share in any single period. Hence we compute the strategy of RA1 in different ranges of the reputation of RA2.

Proposition 4. *The equilibrium strategy at $t = 1$ assuming $p_G = 1$ and $\delta = 1$ is*

$$x_1 = \begin{cases} 0 & \text{if } A \leq \frac{\lambda q_1}{2\left(\lambda q_1 + (1-q_1)\right)} \\ 1 - \frac{(1-2A)\lambda q_1}{2A(1-q_1)} & \text{if } \frac{\lambda q_1}{2\left(\lambda q_1+(1-q_1)\right)} < A < \frac{1}{2} \\ 1 & \text{if } A \geq \frac{1}{2} \end{cases}$$

where A is the solution to the equation

$$\Psi(lie) - \Psi(honest) = I - \delta(2A - \min\{A, B\})I - \delta^2\Big(\lambda(2A - \min\{A, B\})^2 +$$
$$(2B - \min\{A, B\})\big[\lambda(2A - \min\{A, B\}) + 2(1-\lambda)(1-q_2)A + (1-\lambda)q_2 A\big]\Big)I = 0$$

and $B = \frac{\frac{1}{2}\left(s(q_2,1) - \lambda p_G\right)}{p_G(1-\lambda)}$.

Proof. See Appendix 1.8.1 □

Corollary 3. *In equilibrium, x_1 is decreasing in q_1. Moreover, x_1 is increasing in q_2 using first order Taylor approximation.*

Proof. See Appendix 1.8.1 □

Proposition 4 implies that the strategy of RA1 depends on its own and its competitor's reputation. When A is large, RA1 always gives a GR to a bad project. Conversely, when A is small RA1 behaves honestly and gives NR to bad projects. In the intermediate range, RA1 has a mixed strategy, with $0 < x_1 < 1$. Note that the lower threshold for A is increasing with RA1's reputation.

The results imply that RA1 tends to lie less as its reputation increases (Corollary 3). The intuition behind this result is straightforward. Since we assumed $p_G = 1$, the reputation of RA1 goes to zero immediately after a project fails. This means that the cost of lying increases with RA1's reputation while the benefit of lying stays constant. Hence it is not surprising that RA1 prefers to lie less as its reputation increases.[15]

[15] Our results in Section 1.6 show that this is no longer true if $p_G < 1$. The penalty on reputation will be smaller as the reputation of RA increases, *i.e.* the cost of ratings inflation can decrease with reputation, resulting in a 'u-shaped' relationship between strategy and reputation.

Moreover, according to Corollary 3, RA1's strategy tends to increase with RA2's reputation. As explained before, competition has two opposite effects on the behavior of RA1: the disciplining effect and the market-sharing effect. When the reputation of its opponent increases, RA1 will find it less attractive to increase its own reputation given a smaller expected future market share, and hence will behave more laxly. On the other hand, RA1 may have incentives to behave honestly when RA2's reputation increases in order to maintain its market leader position. Our analysis shows that the market-sharing effect tends to dominate the disciplining effect, using first order Taylor approximation. One potential explanation could be that, in our model, the market share of a rating agency is determined not only by its reputation relative to that of its competitor, but also by the absolute level of its reputation. That is, even a monopolistic RA cannot behave totally laxly, because otherwise its reputation would become too low to credibly rate most projects. Therefore, the incentives of a RA to maintain good reputation, even in absence of competition, render the disciplining effect of competition weaker. We believe this is reasonable because in reality, given rational investors, a monopolistic RA would not have unbounded market powers.

However, the results above are based on a three-period model with the assumption that $p_G = 1$, i.e. the strategic RA is caught immediately after the project fails. The results may be driven by the fact that the RAs only live for three periods and hence have limited potential gains associated with higher reputation. In order to capture the long-term benefits of reputation under a more general setting, we move on to the next section, where we relax parameter assumptions and compute numerical solutions in an infinite-horizon case.

1.6 Infinite Horizon Solution

We now present the numerical solution of the model in infinite horizon. The numerical solution is once again computed using backward induction, *i.e.* we first solve the model in the finite period case, and then increase the number of periods so that the equilibrium strategy converges to the infinite horizon solution.

In an infinite period setting, V_t by itself is independent of t. Hence we suppress the time subscript for notational simplicity. However, the reputations evolve over time as investors (and issuers) update their beliefs. Let RA1 be the rating agency that behaves strategically. Then, RA1's value function takes the following form:

$$\begin{aligned} V(q_1, q_2) = \frac{\frac{1}{2}\big(s_1 - \lambda p_G\big)}{(1-\lambda)p_G} \Bigg\{ \lambda\Big[I + p_G\delta V(q_1,q_2) + (1-p_G)\delta V(q_1^F, q_2)\Big] + \\ (1-\lambda)\Big[x_1(q_1,q_2)\big(I + \delta V(q_1^F,q_2)\big) + \big(1 - x_1(q_1,q_2)\big)\delta V(q_1^N, q_2)\Big]\Bigg\} \\ + \frac{s_2 - \frac{1}{2}\big(s_1 + \lambda p_G\big)}{(1-\lambda)p_G} \Bigg\{ \lambda\Big[p_G\delta V(q_1,q_2) + (1-p_G)\delta V(q_1, q_2^F)\Big] + \\ (1-\lambda)\Big[(1-q_2)x_2(q_1,q_2)\delta V(q_1,q_2^F) + \big[q_2 + \big(1-q_2\big)\big(1 - x_2(q_1,q_2)\big)\big]\delta V(q_1, q_2^N)\Big]\Bigg\} \\ + \frac{p_G - s_2}{(1-\lambda)p_G}\delta V(q_1,q_2) \quad (1.11) \end{aligned}$$

where $\frac{\frac{1}{2}\left(s_1 - \lambda p_G\right)}{(1-\lambda)p_G}$ is the probability that the issuer approaches RA1 for rating, $\frac{s_2 - \frac{1}{2}\left(s_1 + \lambda p_G\right)}{(1-\lambda)p_G}$ is the probability that the issuer approaches RA2 and $\frac{p_G - s_2}{(1-\lambda)p_G}$ is the probability that the project is not rated by either RA.

We assume that the model ends at period T and solve the model backwards. We know that the strategic RA will always lie at period T and $T-1$ according to Corollary 2. For all $t < T-1$, the strategy of the RA depends on its own and its competitors' reputation. We solve for the equilibrium strategy of the RA described in Section 1.4. We look at the pay-offs from lying and being honest and determine the strategy. As long as $I + V_t(q_1^F, q_2) > V_t(q_1^N, q_2)$ for $x_t = 1$, RA1 will always choose to lie. Conversely, if $I + V_t(q_1^F, q_2) < V_t(q_1^N, q_2)$ for $x_t = 0$, RA1 will always tell the truth. In all other intermediate cases, there exists a unique x_t *s.t.* $I + V_t(q_1^F, q_2) = V_t(q_1^N, q_2)$ at which RA1 is indifferent between lying or not. Hence we deduce inductively the equilibrium strategies of RA1. As T goes to infinity, we approach the infinite horizon solution. Since $\delta < 1$, the Blackwell conditions are satisfied.

Using this procedure, we solve the model for various parameter values. At the first instance, we solve the model for a monopolistic RA. Next, we introduce competition in the form of RA2 and show that the additional competitive element is not sufficient to discipline the RAs. Furthermore, our results show that competition will in fact increase ratings inflation.

1.6.1 Monopolistic RA

First we consider the case where there is only one RA in the market. In order to make RA1 a monopolist, we set the reputation of RA2 to 0.

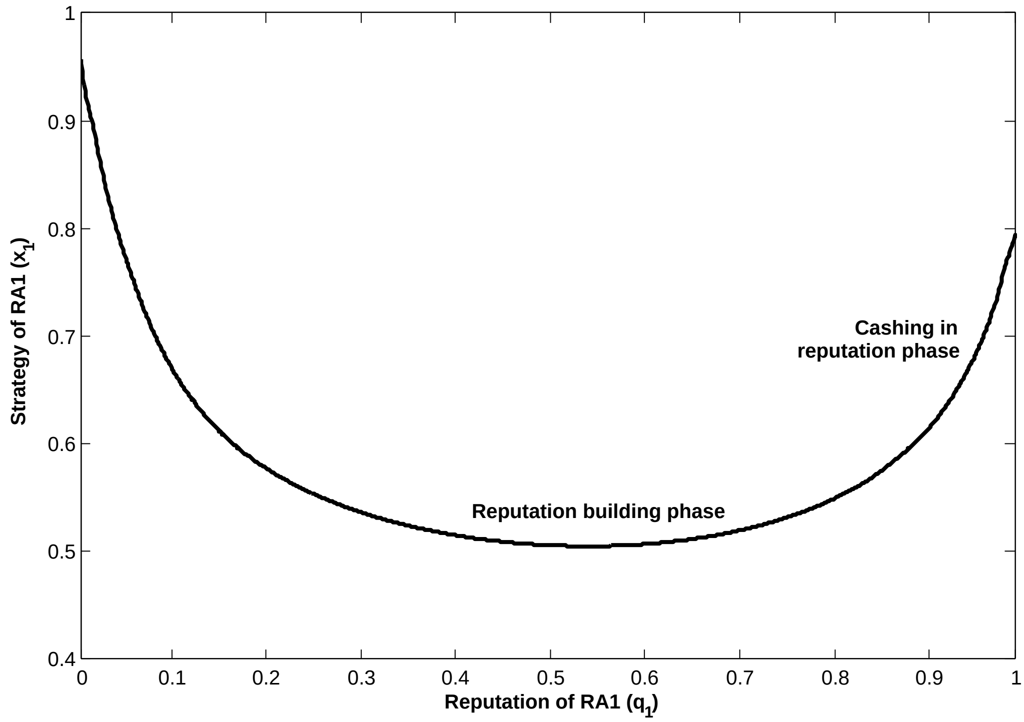
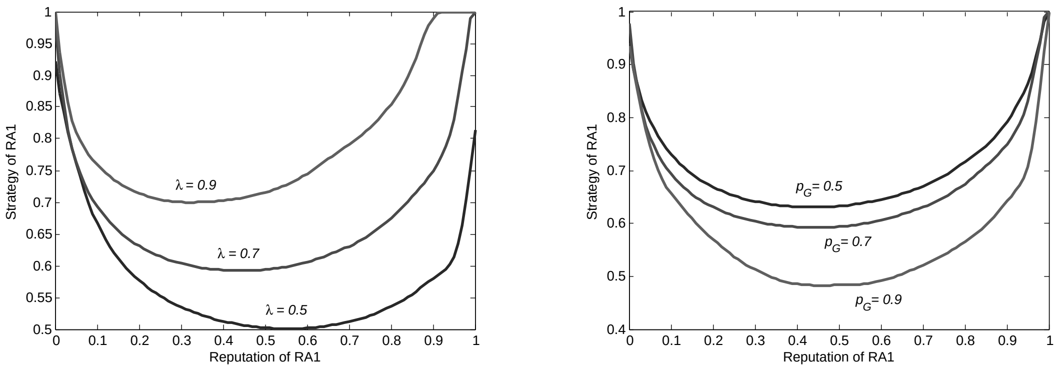


Figure 1.3: Strategy vs Reputation, Monopolistic RA (λ, p_G, δ, q_2) = (0.5, 0.7, 0.9, 0)

Figure 1.3 plots the strategy of the monopolistic RA for parameters (λ, p_G, δ) = (0.5, 0.7, 0.9).[16] We can clearly see the strategy of RA1 is 'u-shaped' in its reputation.

[16]Note that we have chosen this set of parameters (λ, p_G, δ) = (0.5, 0.7, 0.9) for the purpose of illustration only, and verified that our results are robust to other parameter specifications, the plot of which are available upon request. In particular, robustness checks of the main results (Section 1.6.3) are presented in Appendix 1.8.2.

Intuitively, the RA's strategy is determined by the trade-off between current fees and expected future income. When its reputation is very low, the RA's expected future income is very small compared to current fees, hence it has little incentive to behave honestly. When its reputation increases, the RA's future income becomes larger while current fees stay the same, the RA tends to lie less. However, when the RA's reputation is very high, the penalty for lying decreases, and the RA starts to lie more. The reason that the penalty for lying decreases with reputation is that investors attribute project failures to bad luck rather than lax behavior when they believe that the RA is very likely to be of the honest type.



(a) Strategy of RA1 for different values of λ ($p_G = 0.7$)

(b) Strategy of RA1 for different values of p_G ($\lambda = 0.7$)

Figure 1.4: Strategy vs Reputation for different values of λ and p_G ($\delta = 0.9$)

Moreover, we can see from Figure 1.4 that the strategy of RA1 is increasing in λ but decreasing in p_G.[17] The intuition is that, the reputational penalty of lying depends on how the investors update their beliefs. If projects are more likely to be good (higher λ) or if good projects are more likely to fail (lower p_G), then a failure is more likely to be attributed to bad luck rather than lying. Anticipating this smaller cost of lying on reputation, the RA would choose to lie more when λ increases or p_G decreases.

[17] We have also verified that this result holds in the case of competitive RAs, the plots of which are available upon request.

1.6.2 Competitive RA

We now look at the impact of competition on the behavior of rating agencies by introducing a second RA (RA2). Figure 1.5 plots the strategy of RA1 for parameter values $(\lambda,\ p_G,\ \delta) = (0.5,\ 0.7,\ 0.9)$. Figures 1.6 and 1.7 show cross-sections of this figure, for different values of q_2 and q_1 respectively.

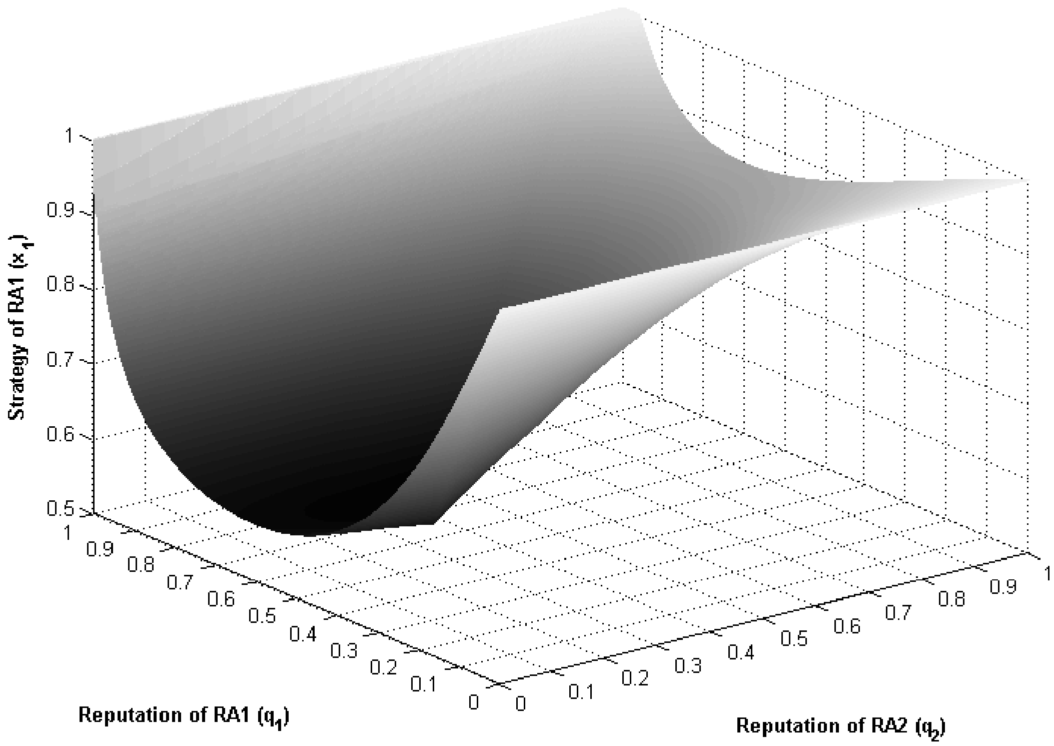
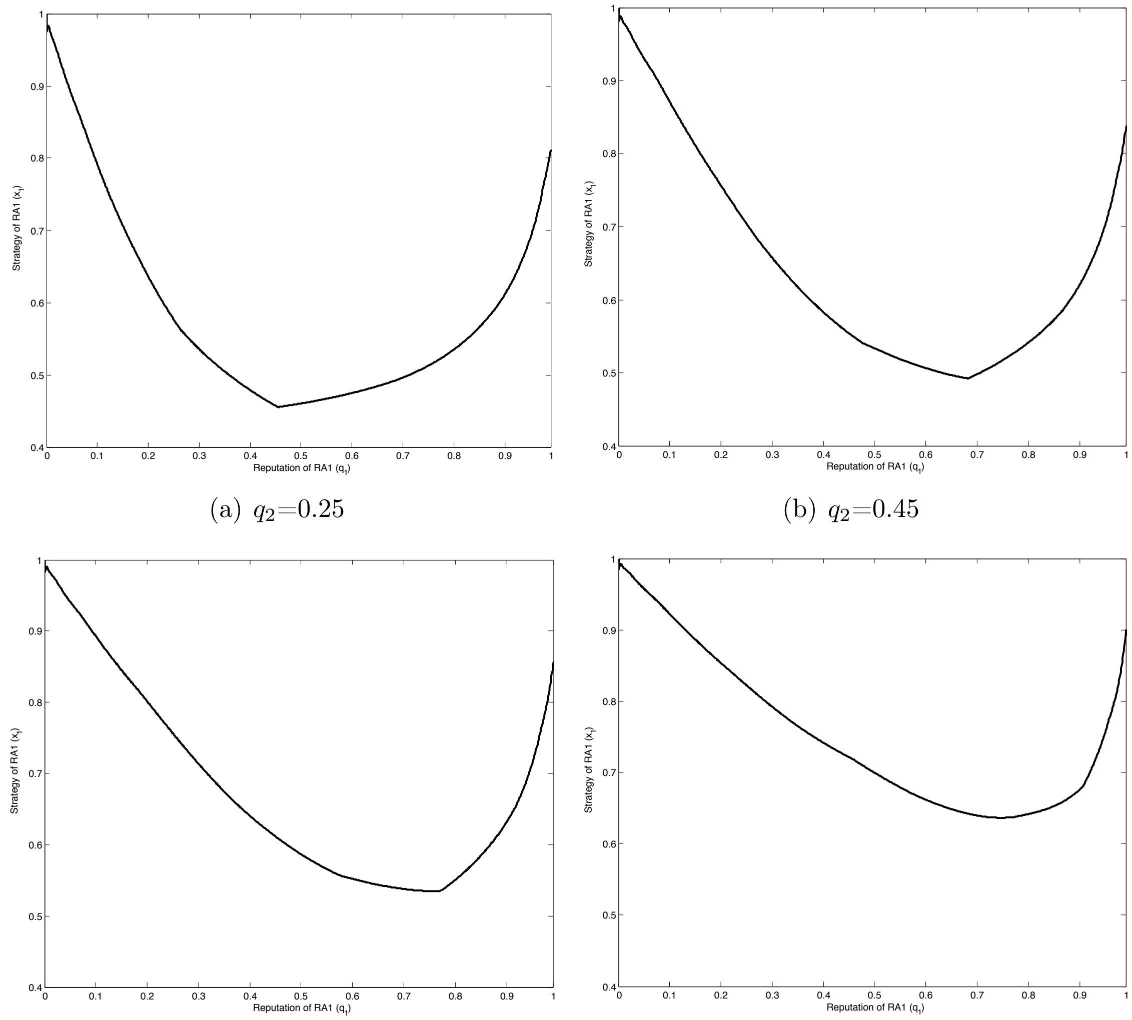


Figure 1.5: Strategy vs Reputation, $(\lambda,\ p_G,\ \delta) = (0.5,\ 0.7,\ 0.9)$

Figure 1.6 shows the relationship between the reputation and strategy of RA1 for different values of the competing RA2's reputation. As we can see, the relationship between the reputation and strategy of RA1 remains 'u-shaped' as in the monopolistic case. Moreover, as the reputation of RA2 increases, the reputation at which RA1 has minimum x_1, *i.e.* is least likely to lie, also increases. This is not surprising as the disciplining effect is greatest when the reputation of the competing RA (RA2) is close to the reputation of RA1. This is because when the RAs' reputations are close, it is more likely that the market leadership will change, resulting in more disciplined behavior. Conversely, if the two RAs have very different reputations, the disciplining effect is relatively weaker.



(a) q_2=0.25

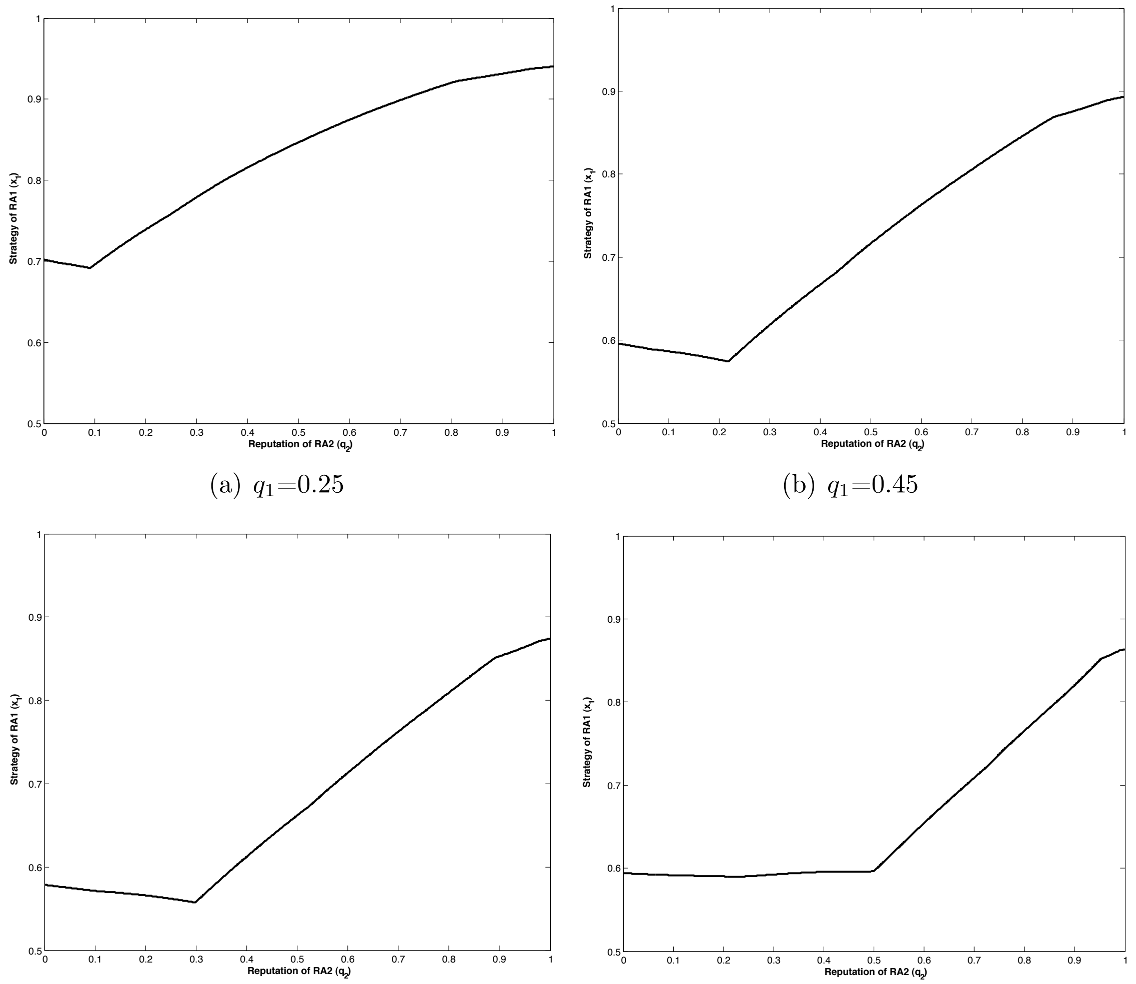
(b) q_2=0.45

(c) q_2=0.55

(d) q_2=0.75

Figure 1.6: Strategy vs Reputation, $(\lambda,\, p_G,\, \delta) = (0.5,\, 0.7,\, 0.9)$, different values of q_2

Moreover, as Figure 1.7 shows, the strategy of RA1 is initially decreasing with or flat in RA2's reputation, and then increasing. This effect of competition is a combination of the disciplining effect and the market-sharing effect. The disciplining effect is strongest when the two RA's reputations are close, and weakest when the two RA's reputations are far apart, which implies that the probability of a change of market leader is very small. On the other hand, the market-sharing effect is always increasing in the competing RA's reputation. When the reputation of RA2 is low, the market-sharing effect is very small as RA2 can only take away a tiny fraction



(a) q_1=0.25 (b) q_1=0.45

(c) q_1=0.55 (d) q_1=0.75

Figure 1.7: Strategy vs Reputation, different values of q_1, $(\lambda,\, p_G,\, \delta) = (0.5,\, 0.7,\, 0.9)$

of market share. As RA2's reputation starts to increase, RA1 tends to lie less as the disciplining effect dominates the market-sharing effect. However, when RA2's reputation goes beyond a certain level, the market-sharing effect dominates as RA2's reputation becomes much higher than RA1's. Hence RA1 will lie more for high values of RA2's reputation, due to the dominance of the market-sharing effect.

Figures 1.8 and 1.9 show the expected profits of RA1 as a function of RA1 and RA2's reputation. We can clearly see that the expected profits of RA1 are increasing in its own reputation, and decreasing in its competitor's reputation, illustrating the market-sharing effect.

Finally, Figure 1.10 shows the convergence dynamics. It plots the change in RA1's

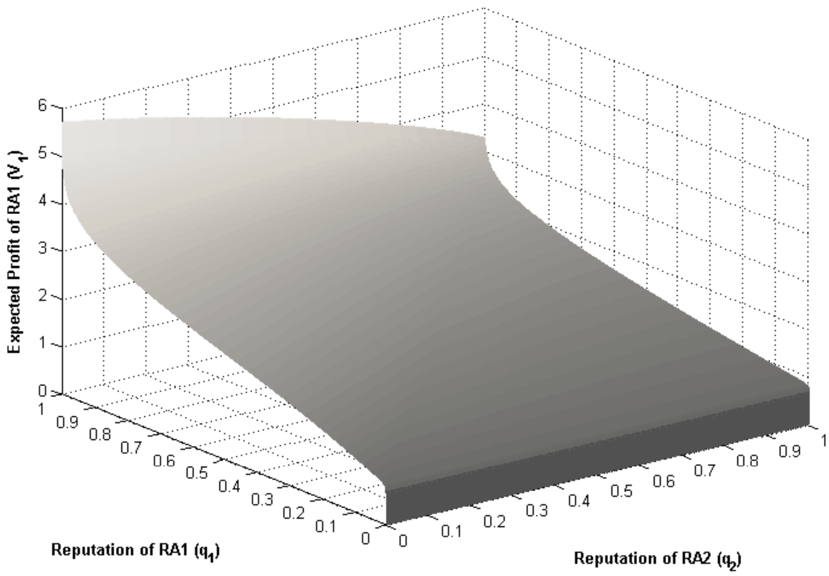


Figure 1.8: Expected Profits vs Reputation, $(\lambda,\, p_G,\, \delta) = (0.5,\, 0.7,\, 0.9)$

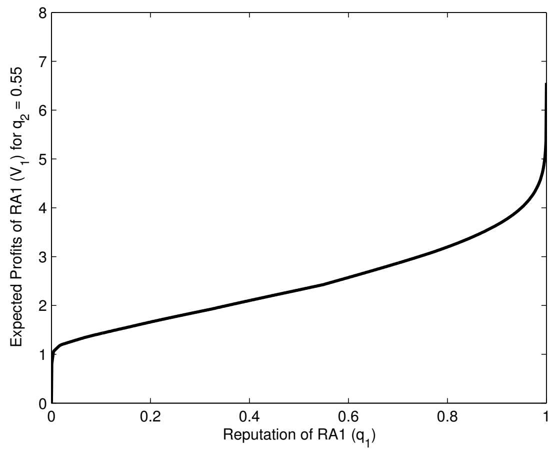
strategy as the number of periods remaining increases. Reputation becomes less and less important as the number of periods remaining declines since there are fewer periods to reap the benefits of higher reputation. Thus ratings inflation increases. Note that as the number of periods remaining increases, the strategy converges, implying that we approach a long (infinite) horizon equilibrium.

In summary, our results show that introducing competition in the form of a second RA is not sufficient to discipline the RAs which always lie with positive probability in equilibrium. We now show that competition will actually increase the lax behavior of RAs and reduce expected welfare.

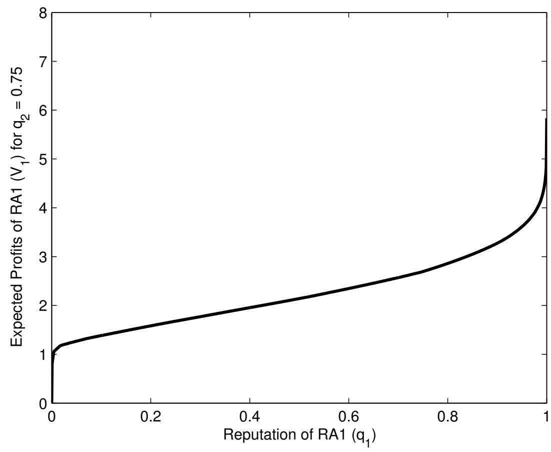
1.6.3 Comparing Monopolistic and Competitive RA

It is often suggested that introducing more competition in the ratings industry can alleviate the problem of improper incentives and ratings inflation. However, our results show that competition is likely to worsen this situation and lead to more ratings inflation.

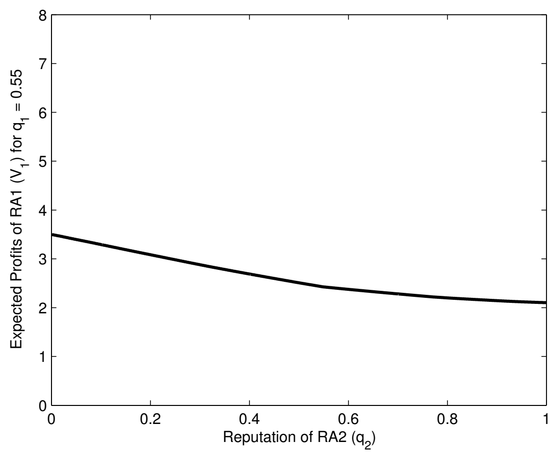
Figure 1.11 compares the strategic behavior of RA1 under no competition, *i.e.* monopolistic RA ($q_2 = 0$), and under a competitive setting with different values of



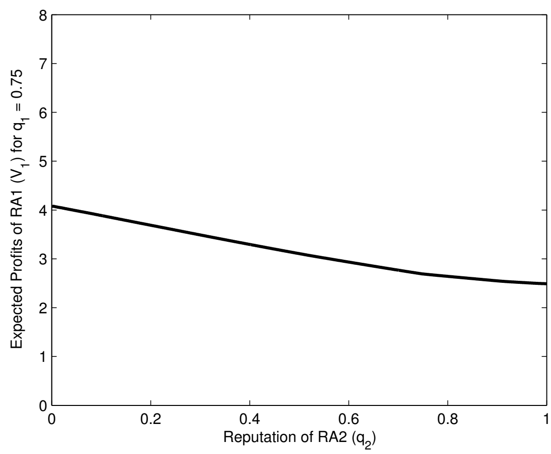
(a) q_2=0.55



(b) q_2=0.75



(c) q_1=0.55



(d) q_1=0.75

Figure 1.9: Expected Profits vs Reputation, different values of q_1 and q_2, $(\lambda, p_G, \delta) = (0.5, 0.7, 0.9)$

q_2. We observe that in most cases, RA1 is prone to greater ratings inflation relative to the monopolistic RA.

As described before, the implication of competition can be divided into the market-sharing effect and the disciplining effect. We can see that the market-sharing effect dominates the disciplining effect (*i.e.* competition aggravates lax behavior) in most cases. The only case where competition may actually alleviate the lax behavior of RA1 is when q_2 is very low (as shown in Figure 1.11(a)). This is because the market-sharing effect is weakest relative to the disciplining effect for low values of q_2. Intuitively, the disciplining effect only depends on the difference between q_1 and q_2, whereas the market-sharing effect increases with the absolute level of q_2. Hence the market-sharing

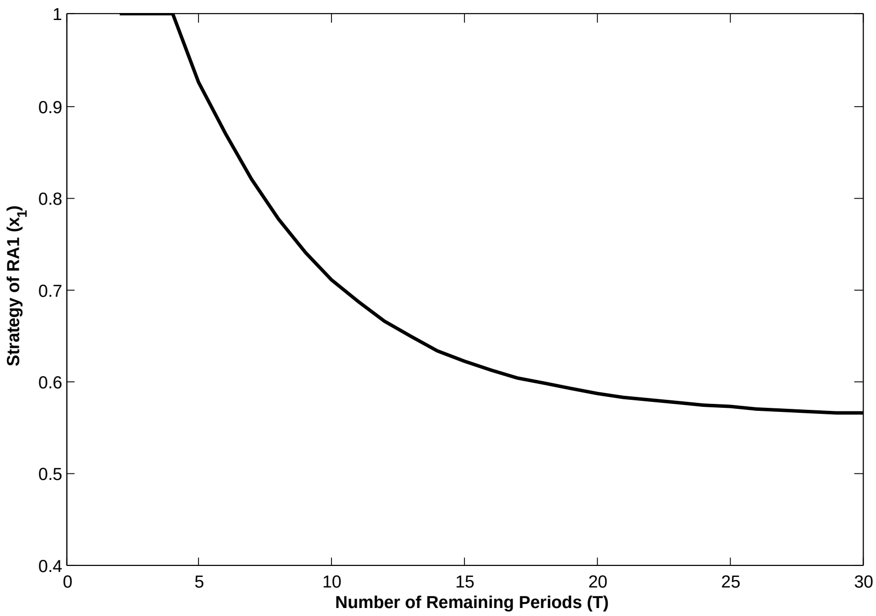


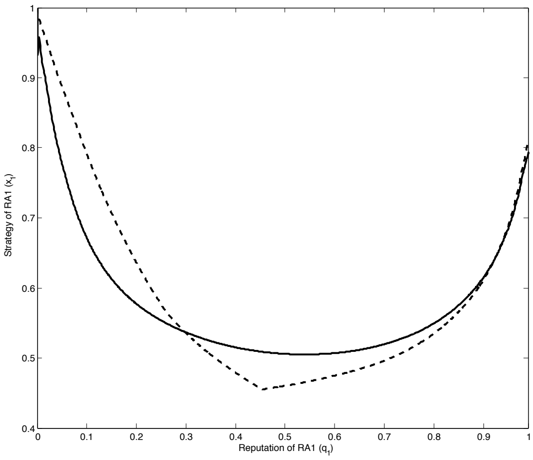
Figure 1.10: Convergence Dynamics of RA1

effect tends to dominate the disciplining effect except for low values of q_2.

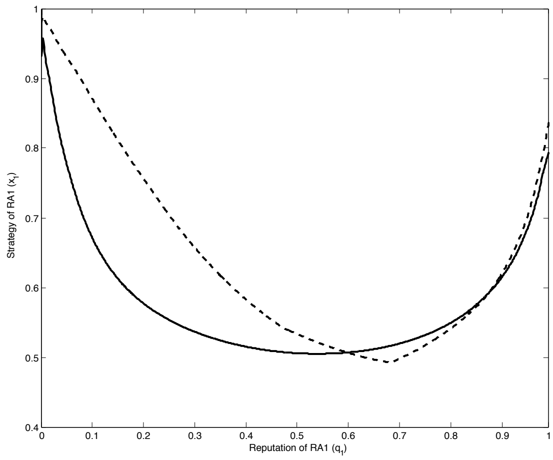
In order to assess the overall impact of competition, we compute the expected increase in lax behavior of RA1 given its own reputation, assuming that the reputation of RA2 is uniformly distributed on $[0, 1]$. A positive value of this measure means the overall effect of enhanced competition on RA1 is to lie more (*i.e* inflate ratings more).

$$\text{Excess Lax behavior of RA1} = \int_{q_2 \in [0,1]} x_1(q_1, q_2)\, dq_2 \;-\; x_1(q_1, 0) \tag{1.12}$$

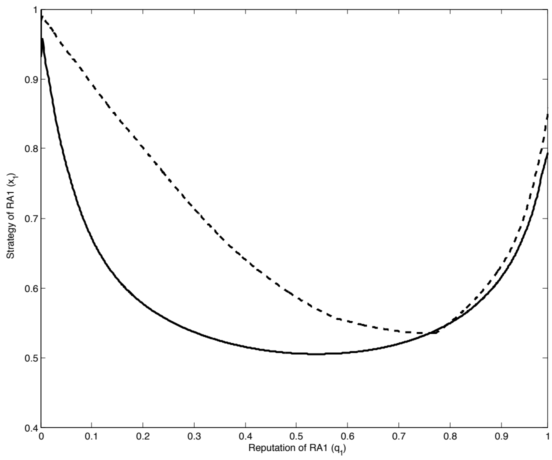
As shown in Figure 1.12, the expected increase in lax behavior of RA1 is always positive, indicating that competition will, in general, aggravate ratings inflation. This is because a smaller market share will tend to reduce the reputational concerns of the RAs, and this market-sharing effect outweighs the disciplining effect brought by competition. Moreover, we can see that the expected increase in lax behavior is increasing for low values of RA1's own reputation and decreasing for high values of RA1's reputation. The intuition is that, when the reputation of RA1 is low, the market share of RA1 is going to shrink significantly after introducing RA2 and the market-sharing effect of competition is strongest. However, when the reputation of



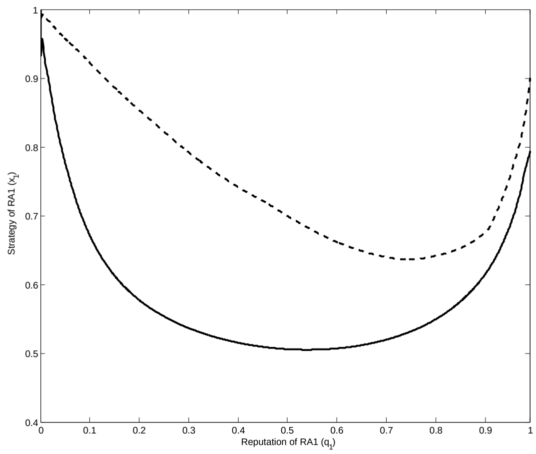
(a) q_2=0.25



(b) q_2=0.45



(c) q_2=0.55



(d) q_2=0.75

Figure 1.11: Comparing Monopolistic and Competitive RA, $(\lambda,\, p_G,\, \delta) = (0.5,\, 0.7,\, 0.9)$
Solid line represents monopolistic RA while dashed line represents competitive RA with different values of q_2

RA1 is high, the impact of introducing RA2 on RA1's market share is small, hence the market-sharing effect becomes weaker and RA1 will lie relatively less. We verify that the excess lax behavior, as defined above, is always positive for other values of λ and p_G in Appendix 1.8.2.

In addition, we measure the expected total welfare in both monopolistic and

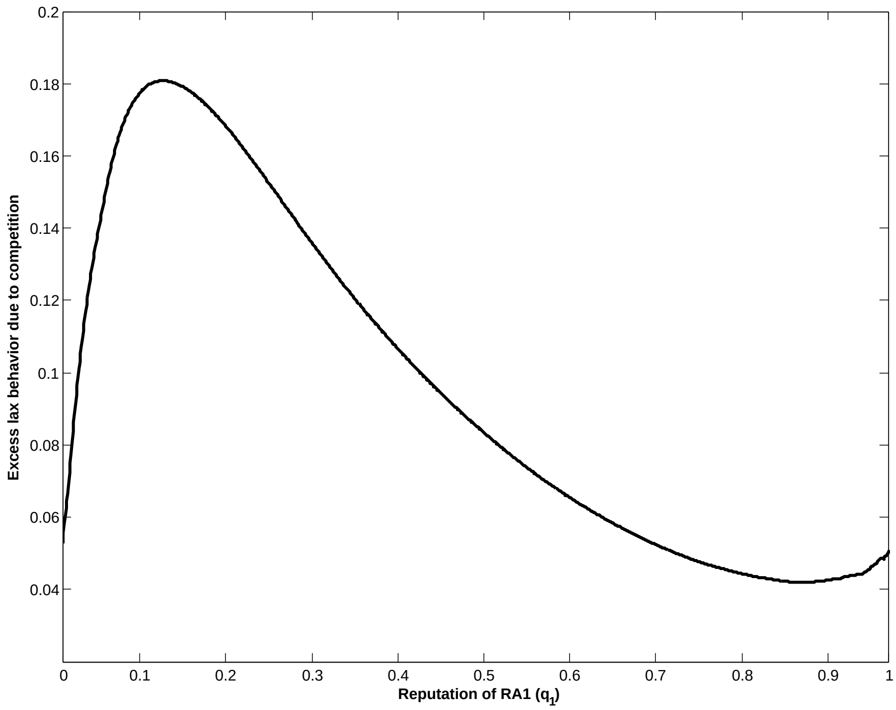


Figure 1.12: Excess Lax Behavior of RA1 due to Competition, (λ, p_G, δ)=(0.5, 0.7, 0.9)

duopolistic settings as defined below.

$$\begin{aligned}\text{Expected Total Welfare} &= E(\text{Project Payoff}) - E(\text{Financing Cost})\\ &= P(\text{RA1 rates})\Big(\lambda p_G \Phi - E(X)\big(\lambda + (1-\lambda)(1-q_1)x_1\big)\Big)\\ &\quad + P(\text{RA2 rates})\Big(\lambda p_G \Phi - E(X)\big(\lambda + (1-\lambda)(1-q_2)x_2\big)\Big)\end{aligned}$$

Figure 1.13 compares the total welfare[18] between the monopolistic case and the duopolistic case where both RAs have the same reputation. We can see that if a new RA is introduced with the same reputation as the incumbent RA, then the total welfare will always decrease, due to the fact that both RAs are more likely to inflate ratings.

Moreover, when we compare in Figure 1.14, the expected total welfare between the monopolistic case and the duopolistic case with fixed values of reputations of RA2, we can see that introducing competition will always lead to lower total welfare as long as the reputation of RA2 is lower than the reputation of RA1. However, total welfare

[18] We are computing the welfare in one period only because it does not depend on time.

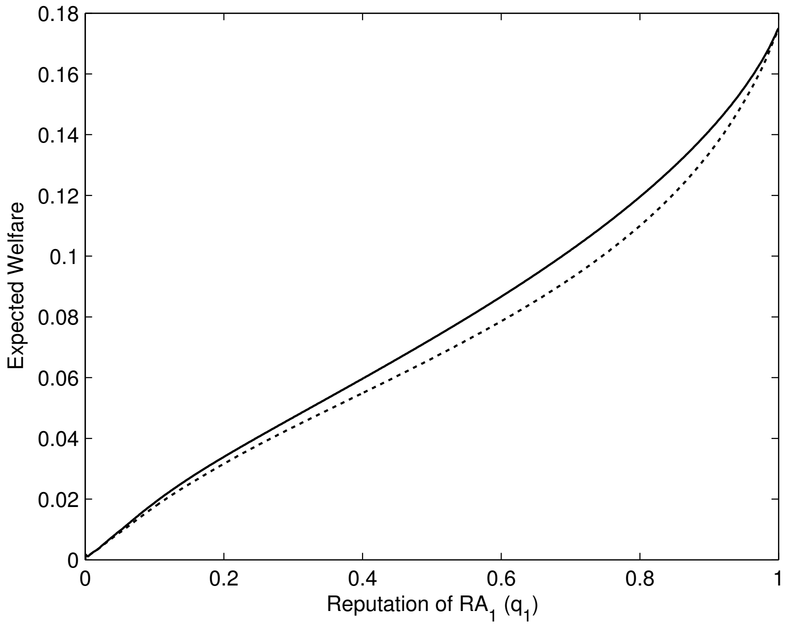
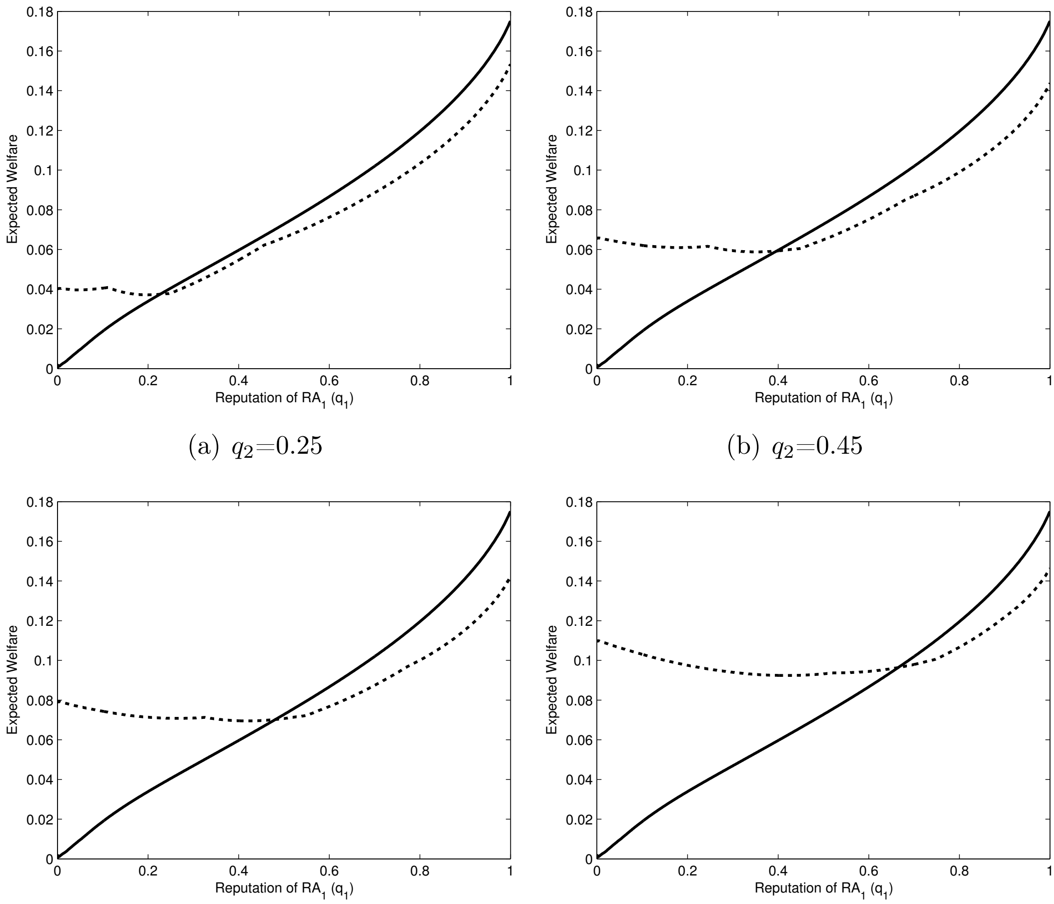


Figure 1.13: Expected Welfare - Competitor has same Reputation
Solid line represents monopoly while dashed line represents duopoly with $q_1 = q_2$

may increase if the entrant RA has a higher reputation than the incumbent. Overall, this implies that competition is likely to adversely impact total welfare, unless we can introduce a new RA with much higher reputation than the incumbent. We check the robustness of this result for different values of λ and p_G in Appendix 1.8.2.



(a) q_2=0.25 (b) q_2=0.45

(c) q_2=0.55 (d) q_2=0.75

Figure 1.14: Expected Welfare - Competitor has different Reputation
Solid line represents monopoly while dashed line represents duopoly for different values of q_2
(λ, p_G, δ) = (0.5, 0.7, 0.9)

1.7 Conclusion

In this paper we show that competition can amplify ratings inflation and the lax behavior of rating agencies, reducing total welfare. This result has important policy implications since it suggests that the most often cited solution to ratings inflation - enhanced competition in the ratings industry - is likely to render the situation worse. While we acknowledge that in order to focus on the implications of competition in the credit ratings industry, we have abstracted from other important issues such as herd behavior, multiple ratings, and the quality of the models used by rating agencies, we believe that our results can serve as a baseline for evaluating the reform proposals currently being discussed.

One of the key thrusts of recent regulatory action in the credit ratings space has been to relax barriers to entry and enhance competition. In the US, the Securities and Exchange Commission has relaxed some barriers to entry and allowed several new CRAs in the US to obtain the Nationally Recognized Statistical Rating Organization (NRSRO) status. The European Union (EU) has gone further and has introduced new requirements as part of the proposed amendments to the EU Regulation on credit rating agencies, the so called 'CRA-III'. The new legislation seeks to place a cap on the market share of each ratings agency and requires issuers to rotate credit rating agencies periodically (see Commission (2011) for details).

In the context of our model, the cap on the market share of rating agencies is likely to incentivize RAs to inflate ratings when their market share is close to the cap since they would no longer benefit from higher reputation. Furthermore, proposals to rotate RAs would mean that RAs would be assured of a market share, irrespective of their reputation. This would break the link between reputation and future income, thereby increasing ratings inflation. More broadly, proposals aimed at artificially enhancing competition are likely to exacerbate the market sharing effect, while doing little to increase the discipling effect.

One of the key findings in our model is that unless the new entrant RA has a higher reputation than the incumbent, increased competition is likely to adversely impact total welfare. However, it is unlikely that a new entrant would have sufficiently high reputation (and hence market share) to challenge the incumbents. It is more plausible to believe that the new entrants would start off as marginal players. Moreover, it is likely that under the current issuer pay model, they will continue to remain marginal players as their low reputation (and associated market share) would incentivize them to inflate ratings more than the established RAs. Interestingly, anecdotal evidence suggests that ratings issued by Dominion Bond Rating Service (DBRS), a relatively new player in the European market, are significantly more lenient than those issued by the more established players.

In conjunction with related work on multiple ratings and herd behavior in the credit ratings industry, our results suggest that a fundamental reorganization of the industry may be required to align the incentives. The conflict of interest highlighted in our paper is fundamental to the issuer-pay model and any meaningful attempt to resolve the conflict would require a fundamental shift in the way rating agencies are compensated. Empirical work by Xia and Strobl (2012) suggests that investor paid RAs can be a solution as they are unlikely to be affected by the conflict of interest highlighted in this paper and can have a discipling effect on the incumbent RAs. However, while an investor pay RAs can be a solution, free riding on the part of investors could result in insufficient revenues for such RAs, making it difficult for them to compete with the incumbents. Deb and Murphy (2009) argue that although free riding is a problem, the increasing use of ratings by institutions, coupled with the rise in the speed of information diffusion in the markets over the last few decades could, with proper regulatory encouragement, ensure that there are investors willing to subscribe to ratings issued by investor pay RAs.

1.8 Appendix

1.8.1 Proofs

Proof of Proposition 1

There exists a unique x_1*, where* $0 \leq x_1 \leq 1$*, given that* $V_t(q_1, q_2)$ *is an increasing function in* q_1*.*

Proof. When the strategic RA (RA1) gets a bad project, it will get pay-off $\Psi(lie) = I + \delta V_t(q_1^F, q_2)$ if it gives the project a GR, and $\Psi(honest) = \delta V_t(q_1^N, q_2)$ if it refuses rating. Note that $q_1^F = \frac{\lambda(1-p_G)q_t}{\lambda(1-p_G)+(1-\lambda)(1-q_1)x_1}$ and $q_1^N = \frac{q_t}{1-x_1(1-q_t)}$, *i.e.* q_1^F is decreasing in x_1 and q_1^N is increasing in x_1. Given that $V_t(q_1, q_2)$ is increasing in q_1, it is easy to see that $\Psi(lie)$ is decreasing in x_1 and that $\Psi(honest)$ is increasing in x_1. Thus if we define x_1 such that

- $x_1 = 1$ if $\Psi(lie) \geq \Psi(honest)$
- $x_1 = 0$ if $\Psi(lie) \leq \Psi(honest)$ for
- $x_1 = x_1^*$ such that $0 < x_1^* < 1$ if $\Psi(lie) = \Psi(honest)$

it follows that x_1 is well-defined and unique. □

Proof of Proposition 2

The strategic RA does not have incentives to give NR to a good project.

Proof. Suppose that the strategic RA (RA1) gets a good project and that its strategy is x_1. Let's examine whether RA1 wants to deviate:

- if $x_1 = 1$, we have $\Psi(lie) \geq \Psi(honest)$, or $I + \delta V_t(q_1^F, q_2) \geq \delta V_t(q_1^N, q_2)$. If the RA1 gives NR to the good project, it will get $\delta V_t(q_1^N, q_2)$, and $I + p_G \delta V_t(q_1, q_2) + (1 - p_G)\delta V_t(q_1^F, q_2)$ otherwise. Since $I + p_G \delta V_t(q_1, q_2) + (1 - p_G)\delta V_t(q_1^F, q_2) \geq I + \delta V_t(q_1^F, q_2) \geq \delta V_t(q_1^N, q_2)$, RA1 does not want to deviate.

- if $x_1 = 0$, $q_1^N = q_1^F = q_1$, hence reputation becomes irrelevant and the RA does not have an incentive to give NR to the good project.

- if $0 < x_1 < 1$, we have $\Psi(lie) = \Psi(honest)$, so $I + p_G \delta V_t(q_1, q_2) + (1 - p_G)\delta V_t(q_1^F, q_2) \geq I + \delta V_t(q_1^F, q_2) = \delta V_t(q_1^N, q_2)$, and hence RA1 does not want to deviate.

Therefore RA1 does not have incentives to give NR to a good project. □

Proof of Corollary 1

Assume $p_G < 1$. Then the equilibrium strategy of the strategic RA is always positive.

Proof. Suppose that the equilibrium strategy is $x_1 = 0$. Then $q_1^N = q_1^F = q_1$ and we must have $I + \delta V_t(q_1, q_2) \leq \delta V_t(q_1, q_2)$. This is impossible as long as $I > 0$. Hence $x_1 = 0$ cannot be an equilibrium strategy. □

Proof of Corollary 2

Suppose the model ends in period T. Then the equilibrium strategy of the strategic RA is $x_t = 1$ at $t = T - 1, T$.

Proof. At $t = T$, the strategic RA does not have any reputational concerns. This implies that the strategy of strategic RA will be to always give GR if the project is bad, *i.e.* $x_T = 1$.

Similarly, at $t = T-1$ the strategic RA will always lie. Suppose that a bad project comes to strategic RA, say RA1. The expected pay-off of RA1 is

$$I + \delta V_{T-1}(q_1^F, q_2) = I + f(q_1^F, 1, q_2, 1)\delta I \tag{1.13}$$

if it lies, *i.e.* gives a good rating, and

$$\delta V_{T-1}(q_1^N, q_2) = f(q_1^N, 1, q_2, 1)\delta I \tag{1.14}$$

if it does not lie, *i.e.* gives no rating, where $f(q_1, x_1, q_2, x_2)$ is the probability that the project comes to RA1 in the next period. Using equations (1.5), (1.6) and (1.7) we have

- $f(q_1, x_1, q_2, x_2) = \frac{\frac{1}{2}\left(s(q_1,x_1) - \lambda p_G\right)}{p_G(1-\lambda)}$ if $s(q_1, x_1) \leq s(q_2, x_2)$
- $f(q_1, x_1, q_2, x_2) = \frac{s(q_1,x_1) - \frac{1}{2}\left(s(q_2,x_2) + \lambda p_G\right)}{p_G(1-\lambda)}$ otherwise

where $s(q, x) = \frac{\lambda p_G}{\lambda + (1-q)(1-\lambda)x}$.

Although in this case RA1 does have reputational concerns, these are not sufficient to prevent RA1 from being lax and not giving GR to bad projects. Since by being honest RA1 is giving up I today, in exchange for having a higher chance of getting I in the next period, it is not optimal for RA1 to be honest, given that RA1 is impatient (*i.e.* $\delta < 1$). Hence the optimal strategy of RA1 is to always lie, i.e. $x_{T-1} = 1$.

□

Proof of Proposition 4

The equilibrium strategy at $t = 1$ assuming $p_G = 1$ and $\delta = 1$ is

$$x_1 = \begin{cases} 0 & \text{if } A \leq \frac{\lambda q_1}{2\left(\lambda q_1 + (1-q_1)\right)} \\ 1 - \frac{(1-2A)\lambda q_1}{2A(1-q_1)} & \text{if } \frac{\lambda q_1}{2\left(\lambda q_1 + (1-q_1)\right)} < A < \frac{1}{2} \\ 1 & \text{if } A \geq \frac{1}{2} \end{cases}$$

where A is the solution to the equation

$$\Psi(lie) - \Psi(honest) = I - \delta(2A - \min\{A, B\})I - \delta^2\Big(\lambda(2A - \min\{A, B\})^2 +$$

$$(2B - \min\{A, B\})\big[\lambda(2A - \min\{A, B\}) + 2(1-\lambda)(1-q_2)A + (1-\lambda)q_2 A\big]\Big)I = 0$$

and $B = \frac{\frac{1}{2}\left(s(q_2, 1) - \lambda p_G\right)}{p_G(1-\lambda)}$.

In addition, x_1 is decreasing in q_1. Moreover, x_1 is increasing in q_2 using first order Taylor approximation.

Proof. Since $p_G = 1$, the reputation of RA1 (*i.e.* the strategic RA) will go to zero if it gives a GR to a bad project since now every good project succeeds and every bad project fails. So the expected pay-off from giving a GR to a bad project is I. This simplifies expressions (1.9) and (1.10) and allows us to derive RA1's equilibrium strategy.

The expected pay-off from being honest is

$$\Psi(honest) = \delta f(q_1^N, 1, q_2, 1)I + \delta^2 \Big(f(q_1^N, 1, q_2, 1)\lambda f(q_1^N, 1, q_2, 1)$$
$$+ f(q_2, 1, q_1^N, 1)[\lambda f(q_1^N, 1, q_2, 1) + (1-\lambda)(1-q_2) f(q_1^N, 1, q_2^F, 1) + (1-\lambda) q_2 f(q_1^N, 1, q_2^N, 1)]\Big) I$$

Using equations (1.6) and (1.7) and noting that RA1 will always lie in periods $t = 2, 3$, this can be rewritten as

$$\Psi(honest) = \delta(2A - \min\{A, B\})I + \delta^2 \Big(\lambda (2A - \min\{A, B\})^2$$
$$+ (2B - \min\{A, B\})[\lambda(2A - \min\{A, B\}) + 2(1-\lambda)(1-q_2)A + (1-\lambda)q_2 A] \Big) I$$

where $A = \frac{\frac{1}{2}\left(s(q_1^N, 1) - \lambda p_G\right)}{p_G(1-\lambda)}$ and $B = \frac{\frac{1}{2}\left(s(q_2, 1) - \lambda p_G\right)}{p_G(1-\lambda)}$

The expected pay-off from lying is I, since the RA's reputation goes to zero

$$\Psi(lie) = I$$

We look for a equilibrium of the game by examining RA1's trade-off between lying and not lying. If the pay-off from lying is greater when $x_1 = 1$, we have a pure-strategy equilibrium in which RA1 always lies; if the pay-off from not lying is greater when $x_1 = 0$, we have a pure-strategy equilibrium in which RA1 never lies; otherwise we have a mixed-strategy equilibrium in which RA1 is indifferent between lying or not given some prior beliefs about its strategy, *i.e.* $0 < x_1 < 1$.

We now solve the equation $\Psi(lie) - \Psi(honest) = 0$. We do this in 2 stages. In the first stage, we solve the equation in terms of A and then using the expression for

A, we solve for the equilibrium value of x_1.

For $A < B$ we have

$$\Psi(lie) - \Psi(honest) = \delta^2(1-\lambda)(2-q_2)A^2 - \big(\delta + 2B\delta^2\lambda + 2B\delta^2(1-\lambda)(2-q_2)\big)A + 1$$

Assuming $\delta = 1$, the solution is

$$A = B + \frac{1 + 2B\lambda - \sqrt{(1+2B\lambda)^2 + (1-\lambda)(2-q_2)\varrho}}{2(1-\lambda)(2-q_2)}$$

which is valid[19] as long as $\varrho = B^2\big(2 - (1-\lambda)q_2\big) + B - 1 > 0$.

Note that B can be simplified to

$$B = \frac{\lambda q_2}{2\big(1 - q_2(1-\lambda)\big)}$$

We can see that B is bounded above by $\frac{1}{2}$. Therefore $\varrho \leq 0$ and we can rule out the case above.

Now for $A \geq B$ we have

$$\Psi(lie) - \Psi(honest) = -4\delta^2\lambda A^2 - \big(2\delta - 2B\delta^2\lambda + B\delta^2(1-\lambda)(2-q_2)\big)A + \delta B + 1$$

Assuming $\delta = 1$, the solution is

$$A = B + \frac{\sqrt{\big(2 + 6\lambda B + B(1-\lambda)(2-q_2)\big)^2 - 16\lambda\varrho} - \big(2 + 6\lambda B + B(1-\lambda)(2-q_2)\big)}{8\lambda}$$

[19] *i.e.* A is real and less than B.

which is valid[20] given $\varrho = B^2\big(2-(1-\lambda)q_2\big) + B - 1 \leq 0$.

Note that A can also be expressed as

$$A = \frac{\sqrt{\big(2-2\lambda B + B(1-\lambda)(2-q_2)\big)^2 + 16\lambda(B+1)} - \big(2-2\lambda B + B(1-\lambda)(2-q_2)\big)}{8\lambda}$$

Applying first-order Taylor approximation[21], we have

$$A \simeq \frac{B+1}{2-2\lambda B + B(1-\lambda)(2-q_2)} = \frac{B+1}{2-2\lambda B + \frac{\lambda q_2}{2} + B(1-2\lambda)}$$

Substituting for B, the first order derivative of A with respect to q_2 is

$$\frac{\lambda\Big((1-\lambda)(3\lambda-2)q_2^2 + 4(1-\lambda)q_2 + 8\lambda\Big)}{\Big(4 - q_2(4\lambda^2 - 6\lambda + 4) - \lambda(1-\lambda)q_2^2\Big)^2}$$

It can be shown that the minimum of the above is proportional to $-\frac{4(1-\lambda)}{3\lambda-2} + 8\lambda$ and is attained when $q_2 = -\frac{2}{3\lambda-2}$. When $\lambda < \frac{2}{3}$, the minimum is always positive, hence A is increasing in q_2. When $\lambda > \frac{2}{3}$, the derivative reaches zero when $q_2 = \frac{-4(1-\lambda)\pm\sqrt{\left(16(1-\lambda)^2 - 32\lambda(1-\lambda)(3\lambda-2)\right.}}{2(1-\lambda)(3\lambda-2)}$, which is negative. Hence the minimum is positive for $q_2 > 0$. Therefore A is always increasing in q_2.

Now we have shown that there always exists a solution which depends on the parameter ϱ. Since A always has a solution, we can use it to find the equilibrium strategy x_1 in terms of A, *i.e.* we will look for the value of x_1 such that $\frac{\frac{1}{2}\left(s(q_1^N,1) - \lambda p_G\right)}{p_G(1-\lambda)} = A$.

Note that assuming $p_G = 1$ implies $\lambda p_G = \lambda$. Using this and equation (1.5), the

[20] *i.e.* A is real and greater than B.
[21] That is, $\sqrt{N^2+d} \simeq N + \frac{d}{2N}$.

above expression can be rewritten as $\frac{\lambda q_1^N}{\lambda q_1^N + 1 - q_1^N} = 2A$, where $q_1^N = \frac{q_1}{1-(1-q_1)x_1}$.

Solving, we obtain

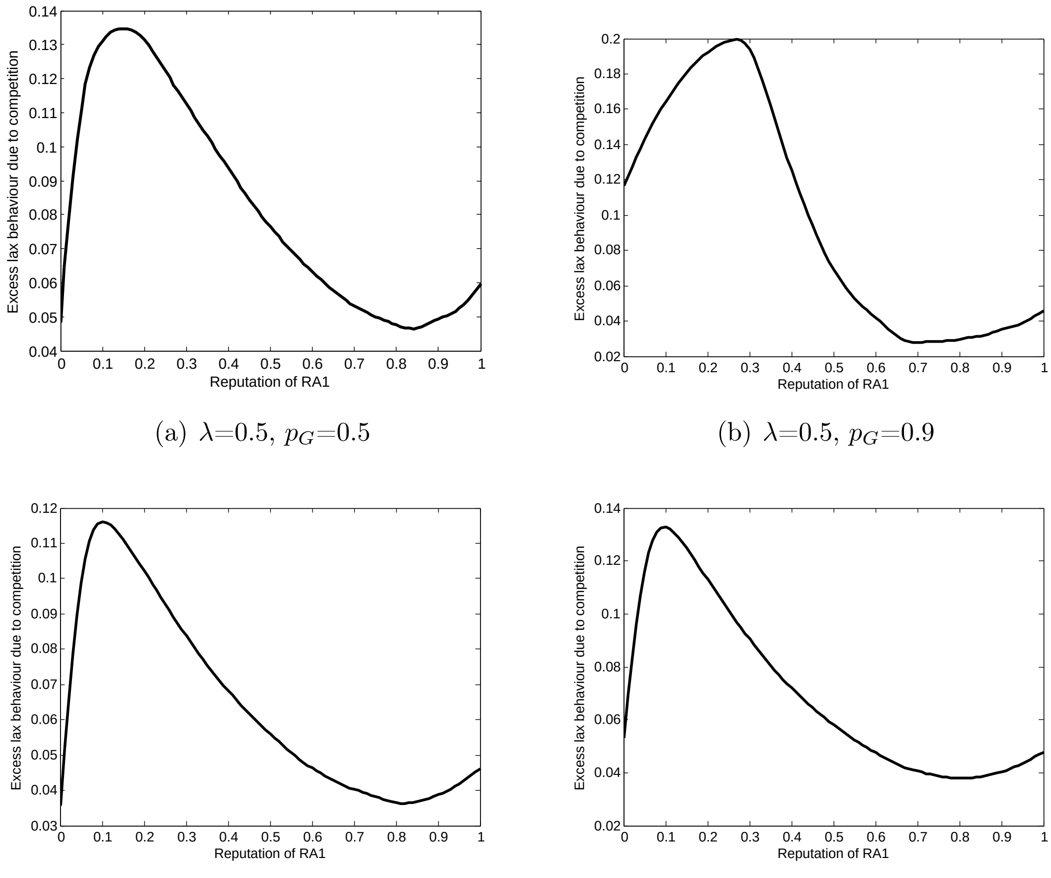
$$x_1 = 1 - \frac{(1-2A)\lambda q_1}{2A(1-q_1)}$$

for $0 < x_1 < 1$. This holds when $\frac{\lambda q_1}{2\left(\lambda q_1 + (1-q_1)\right)} < A < \frac{1}{2}$. Clearly, we have x_1 increasing in A and decreasing in q_1.

□

1.8.2 Robustness Check

Excess Lax behavior



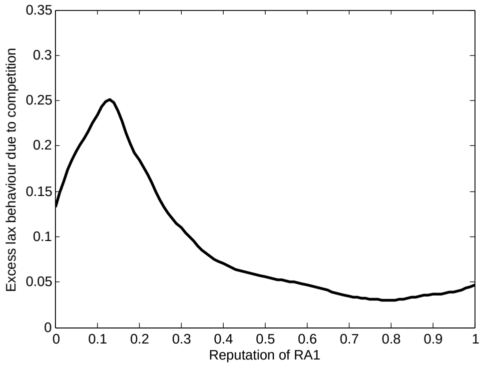
(a) λ=0.5, p_G=0.5

(b) λ=0.5, p_G=0.9

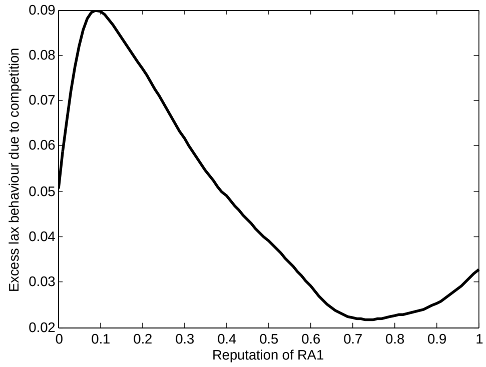
(c) λ=0.7, p_G=0.5

(d) λ=0.7, p_G=0.7

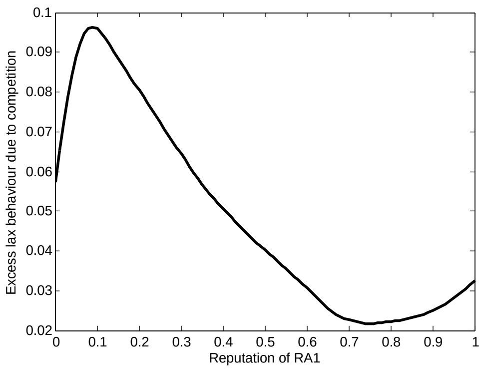
Figure 1.15: Excess Lax behavior for different values of λ and p_G ($\delta = 0.9$)



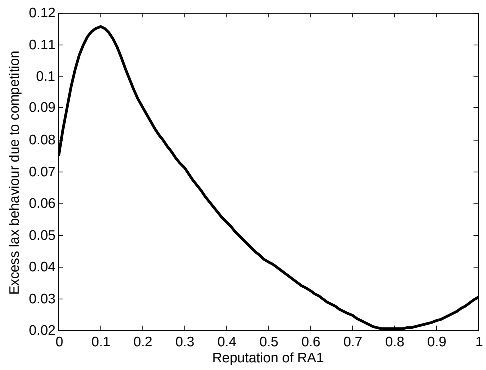
(a) λ=0.7, p_G=0.9



(b) λ=0.9, p_G=0.5



(c) λ=0.9, p_G=0.7



(d) λ=0.9, p_G=0.9

Figure 1.16: Excess Lax behavior for different values of λ and p_G (continued)

Expected Total Welfare

The reputation of RA1 (q_1) above which the expected total welfare is always greater in the monopoly case than in the duopoly case, for different values of q_2 ($\delta = 0.9$)

Parameter values	$\mathbf{q_2 = 0.25}$	$\mathbf{q_2 = 0.45}$	$\mathbf{q_2 = 0.55}$	$\mathbf{q_2 = 0.75}$
$\lambda = \mathbf{0.5}$, $\mathbf{p_G = 0.5}$	$q_1 = 0.23$	$q_1 = 0.45$	$q_1 = 0.52$	$q_1 = 0.69$
$\lambda = \mathbf{0.5}$, $\mathbf{p_G = 0.7}$	$q_1 = 0.23$	$q_1 = 0.45$	$q_1 = 0.52$	$q_1 = 0.69$
$\lambda = \mathbf{0.5}$, $\mathbf{p_G = 0.9}$	$q_1 = 0.23$	$q_1 = 0.45$	$q_1 = 0.52$	$q_1 = 0.69$
$\lambda = \mathbf{0.7}$, $\mathbf{p_G = 0.5}$	$q_1 = 0.15$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.67$
$\lambda = \mathbf{0.7}$, $\mathbf{p_G = 0.7}$	$q_1 = 0.15$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.67$
$\lambda = \mathbf{0.7}$, $\mathbf{p_G = 0.9}$	$q_1 = 0.15$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.67$
$\lambda = \mathbf{0.9}$, $\mathbf{p_G = 0.5}$	$q_1 = 0.13$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.66$
$\lambda = \mathbf{0.9}$, $\mathbf{p_G = 0.7}$	$q_1 = 0.13$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.66$
$\lambda = \mathbf{0.9}$, $\mathbf{p_G = 0.9}$	$q_1 = 0.13$	$q_1 = 0.45$	$q_1 = 0.51$	$q_1 = 0.66$

Chapter 2

The Effects of Fund Flows on Corporate Investment: a Catering View

2.1 Introduction

Stock prices are positively related to corporate investment. Firms with strong fundamentals are associated with higher stock prices and higher investment, but is the non-fundamental component of stock prices related to corporate investment? In other words, when stock prices depart from fundamentals, are there any real effects? In particular, is there any relation between high stock prices and the execution of value-destroying projects for firms that are not financially constrained? This chapter provides evidence that uninformative stock demand exerted by extreme mutual fund flows prompts firm managers to overinvest.

In principle, firm managers maximize the long-term value of the firm's assets and only execute positive net present-value projects. However, Stein (1996) shows that firm managers with incentives to maximize the current stock price might execute value-destroying projects. To illustrate this mechanism, consider a software firm with very little or no debt and plentiful internal funds. In recent years, the firm has delivered a series of very successful products; however, lately, its active research and development (R&D) department has failed to offer any suitable projects, an issue acknowledged by the firm manager. Mutual funds with an important stake in the firm have been investing and collecting high returns in recent years, and retail investors[1] have been moving money into mutual funds that hold the firm's stock. The firm manager knows that the company's mutual fund shareholders believe that the firm's prospects are better than they actually are, and she must decide whether to invest in value-destroying projects. She knows that the firm's shareholders have a short-term horizon and will sell their stakes before any information about the quality of the project becomes public, a process that takes particularly long in a software firm with opaque assets. If the firm manager invests, the stock price will rise temporarily, and before the price reverts, the firm's shareholders will have cashed in on the artificial rise in prices. By contrast, however, if the manager maximizes the long-term value of the firm, she will not invest in value-destroying projects, and the stock price will not move. Therefore, if her objective is to maximize the current share price, she will cater to shareholders' expectations by investing. The main focus of this chapter is the empirical question of whether uninformative mutual fund flows lead managers of non-financially constrained firms to overinvest.

In this chapter, I use Coval and Stafford (2007)'s mutual fund flow-related variable to measure stock price pressure. Firms whose stocks are bought by funds under extreme inflows are high price pressure firms and have lower expected future stock returns. The price pressure measure is particularly suited for testing the catering channel of investment for the following reasons: (i) price pressure is beyond the firm manager's control; that is, she is unlikely to have any influence on the portfolio allocation of the mutual funds that invest in her firm; (ii) the reversal pattern in stock returns associated with price pressure takes longer than 2 years, a period long enough to influence the investment decision by the firm manager; (iii) price pressure contains the two ingredients of a stock mispricing variable, i.e., a pattern that consistently

[1] Retail investors are those who invest in and have quotas in mutual funds.

drives stock prices away from fundamentals and a certain degree of limits to arbitrage that impede arbitrageurs from stepping in and driving prices back to fundamentals[2].

To empirically study the firm manager's investment decision when faced with stock price pressure, I implement tests that unveil an investment pattern that is not necessarily driven only by the firm's financing needs. After establishing that lagged price pressure is positively correlated with investment, I show that: (i) high price pressure high investment firms have lower future performance, which is consistent with firm managers executing value-destroying projects; (ii) the investment sensitivity to price pressure remains positive and significant for firms that are less financially constrained; (iii) firms with short term shareholders have a stronger investment sensitivity to price pressure. I describe the results below.

First, I test and show that lagged price pressure is associated with higher firm investment, suggesting that a proxy for the non-fundamental component of stock prices influences the firm's investment policy. Although the price pressure variable is quite exogenous to the fundamentals of the firm, the result is partially driven by investment opportunities, a finding that is cause for concern. To address this concern, I control for the following items: (i) Tobin's Q, which many studies use as a proxy for a firm's fundamentals; (ii) cash flow, an important determinant of a firm's investment; and (iii) past stock returns, which capture the information component of the price pressure variable. Even after implementing these controls, the investment to price pressure sensitivity remains positive, significant and economically important. Specifically, I find that the main regressor coefficient of lagged price pressure is 5.285 (t=4.17) in the specification without past stock returns and 3.680 (t=2.79) when

[2]The mutual fund industry is particularly prone to performance-based arbitrage à la Shleifer and Vishny (1997). By moving flows into mutual funds with recent superior past performance - *the smart money effect* - retail investors create price pressure on the stocks held by those mutual funds, driving them away from fundamentals, as studied by Vayanos and Woolley (2011) and Lou (2010). The latter author also shows that predictable demand shocks to individual stocks are not fully eliminated by arbitrageurs, which is consistent with the limits of arbitrage in this setting.

including past stock returns from 60 months to 1 month before the beginning of the investment period. These results are also economically relevant. In the specification with past stock return controls, one standard deviation increase in the lagged price pressure variable leads to an increase of 1.27% of investment as a proportion of lagged capital, which is equivalent to 1.59% standard deviations and to 5.78% of the median of the same investment variable.

Second, I examine whether high price pressure firms adopt value-destroying projects. I run Fama and MacBeth (1973)'s regressions on future stock returns from 6 to 18 months after the end of the investment period as a dependent variable, finding that the estimated coefficient of the interaction between the price pressure and investment is negative and significant, consistent with high price pressure high investment firms having lower future stock returns. One interpretation of this result is that high price pressure firms that invest too much are executing more value-destroying projects than other high price pressure firms that invest relatively less. Additionally, I use operational performance as a dependent variable, proxied by the future change in return on assets, which leads to a similar result.

Third, I study a subset of firms that do not depend on external financing and investigate whether their investment policies respond to stock price pressure. I split the sample into relatively financially constrained and unconstrained firm-years according to two indices of financial constraints: the Kaplan and Zingales (1997) KZ index and the Hadlock and Pierce (2010) SA index. In both cases, I find that investment sensitivity to price pressure is positive and significant for the two subsamples of firms and higher for the relatively financially unconstrained firms. I also examine the investment policies of financially unconstrained firms using a subsample of firms that do not conduct seasoned equity offerings (SEOs) from 1 year before the start of the investment period until the end of the period. The results of this examination show that the estimated coefficient for the investment sensitivity to price pressure remains positive and significant. In addition, I include cash from equity issuance as a control in all tests implemented in this study and find that the results are largely robust. The overall findings reveal that investment is sensitive to lagged stock price pressure for less financially constrained firms and firms that are not engaging in SEOs. These results seem to suggest that there is an operating catering channel of investment for firms that do not rely on issuing external securities.

Finally, I test whether investment sensitivity to stock price pressure is stronger when the firm manager has incentives to maximize the current stock price. In particular, firms with short-term shareholders and opaque assets tend to be responsive to steeper short-term incentives. I observe short-term shareholders and long-term shareholders, classifying the groups using a mutual fund churn rate measure. Stocks that are held by higher-churning funds are held by short-term shareholders. I split the sample into two groups, high and low churn rate firm-years. I find that investment sensitivity to price pressure is stronger for high churn rate firms, i.e., firms with short-term shareholders. Along the same lines, I divide the sample into opaque and non-opaque firms. The sample is split into firm-years with high and low R&D intensity. Firms with high R&D expenses as a proportion of total assets reportedly have a less transparent investment process and are harder to value, contributing to a stronger catering mechanism. Indeed, regression estimates for the high R&D intensity subsample are higher when measuring the investment sensitivity to price pressure. These results are consistent with a stronger direct link between stock price pressure and investment when a firm manager has incentives to maximize the current share price.

The chapter continues as follows. In the next section, I relate this chapter to other studies in the literature. In Section 2.3, I present the theoretical basis for the catering mechanism and explain how it translates into testable empirical hypotheses. In Section 2.4, I describe the mutual fund and accounting datasets, their merging procedure and the screening devices I use before forming the final dataset at the firm-year level. I also define stock price pressure and describe its association with a reversal pattern. Section 2.5 describes the empirical strategy and reports the results. In Section 2.6, I show that the results hold true amid concerns regarding error measurements and, additionally, that the results are robust when considering different definitions of the price pressure variable. Section 2.7 presents the study's conclusions.

2.2 Related Research

This chapter's findings complement the literature on the real effects of equity mispricing. This study is mostly related to the work of Polk and Sapienza (2009), who provide evidence of an operating catering channel of investment by showing that discretionary accruals are positively related to abnormal investment. I build on their study by examining how extreme flows into funds that own a stake in the firm shape firm managers' investment policy. My test has an important innovation, in that while they use discretionary accruals as a proxy for equity mispricing, which is set by firm managers, I use mutual fund flow-driven equity mispricing, which is exogenous to firm managers' decision sets.

Another related study by Baker, Stein and Wurgler (2003) shows that firm investment is positively related to Tobin's Q and that the sensibility monotonically increases with the degree of financial constraints, as measured by the KZ index. In their findings, stock mispricing proxied by Tobin's Q influences firm investment through external financing; the financial constraint is relaxed, and the firm is able to issue external securities to finance positive net present value projects that previously lacked funding. In contrast, the catering channel documented in the present chapter is related to financially unconstrained firms that invest in negative net present value projects when the firm manager has incentives to maximize the current stock price and shareholders expect the firm to have better prospects than it actually has. Stock mispricing has a direct influence on firm investment, in opposition to the indirect market timing channel, as documented by the three authors.

This chapter adds to the literature testing whether stock prices have an effect on firm investment over and above fundamentals. In addition to Stein (1996), studies that provide theoretical support on the effects of stock prices on investment include Farhi and Panageas (2004) and Gilchrist, Himmelberg and Huberman (2005). On the empirical side, earlier studies tended to regress firm investment using stock price and a measure of firm fundamentals such as Tobin's Q. When explaining firm investment, Barro (1990) finds that the stock price outperformed Q, whereas Morck, Shleifer and Vishny (1990) suggest instead that stock markets are a sideshow and do not influence firm managers' decisions to invest over and above fundamentals. The approach used in the present chapter is more closely related to recent studies on the real effects of stock mispricing; these studies examine the effects of a direct measure of stock mispricing on firm investment.

This study is also linked to other papers that investigate firm managers' catering decisions, which are any corporate actions intended to boost share prices. Baker and Wurgler (2004) and Li and Lie (2006) study the effects of catering on dividends. Cooper (2001) and Cooper, Khorana, Osobov, Patel and Rau (2005) find evidence that firms that changed to more "Internet-sounding" names during the dotcom bubble increased their value. Aghion and Stein (2008) investigate whether catering incentives influence firm managers' decisions on how to maximize growth or cut costs.

Another strand of research studies how stock prices influence firm investment through learning. This research argues that firm managers learn from stock prices and base their investment decisions on them. Chen, Goldstein and Jiang (2007) test this theory, finding that the amount of private information incorporated into stock prices has a strong positive effect on the sensitivity of firm investment to stock prices. In contrast, the present chapter studies a set of firm managers with short-horizon incentives in financially unconstrained firms; hence, these managers are unlikely to learn from prices. In other words, the set of firms that is prone to catering is quite uncorrelated with the set of firms whose managers learn from prices.

This study relates to other research that uses equity mutual fund flows as an instrument to identify stock price pressure, including studies by Coval and Stafford (2007); Frazzini and Lamont (2008); Lou (2010), Khan, Kogan and Serafeim (2012); Hau and Lai (2011); Edmans, Goldstein and Jiang (2012); and Sulaeman and Wei (2012). Recent studies finding that stock misvaluation leads to an increase in firm investment include those by Gao and Lou (2011), Hau and Lai (2012) and Birru (2012), although these studies identify a channel that relies on external financing and focus on different strategies that do not exploit the catering channel of investment. In contrast, Bakke and Whited (2010)'s study suggests that firm investment is not influenced by stock mispricing.

2.3 Mechanism

The mechanism in this study is inspired by the Polk and Sapienza (2002)'s model of catering of investment, which predicts that firm managers overinvest (underinvest) if the stock is overpriced (underpriced).

Two types of agents include firm managers and mutual fund shareholders, both which are risk-neutral. The firm manager maximizes the wealth of the average shareholder. There is one project in which the firm manager might or might not invest. The quality of the project is good or bad, but only the firm manager sees the quality before the investment decision is made. The discovery process regarding the quality of the project depends on the opaqueness of the firm's assets. In more opaque firms, it takes longer for shareholders to find out whether the project is good or bad. Shareholders derive all of their wealth from the sale of their stocks. They experience one stochastic liquidity shock that prompts them to sell all their holdings in the firm.

Mutual fund shareholders are bound to act as their retail investors lead them; when there are extreme outflows, shareholders must sell their existing stock positions to meet their redemptions. When there are extreme inflows, mutual fund shareholders increase their existing stock positions.[3]

A good project enhances value, whereas a bad project destroys value. Hence, the efficient decision is to invest only if the project is good. However, if shareholders have early liquidity shocks, the manager might make inefficient decisions to maximize the wealth of the average shareholder. The intuition is as follows. Consider the case of an opaque firm, for which it takes shareholders longer to find out whether a project is good or bad. Also assume that shareholders have, on average, short-term liquidity needs, in the sense that most of them are likely to sell their stocks before knowing the quality of a project. Furthermore, suppose that mutual fund shareholders under extreme inflows own some of the firm's stock, which becomes considerably overpriced.

Retail investors who invest in the mutual funds holding the firm's stocks do not know the quality of the project currently being invested in by the firm; however, the investors assume the quality is good because the firm has been delivering consistently good projects in recent years. If the manager believes the project is good, he makes the efficient decision and invests. However, if the project is bad, to maximize the wealth of the average shareholder, the manager should make an inefficient decision and invest; this decision will lead to an increase in the stock price because retail investors will believe that a value-enhancing project is being put into place. The manager knows that once the quality of the project is revealed, the stock price will fall; however, because the mutual fund shareholders have had early enough liquidity shocks, the early increase in the stock price more than compensates for its subsequent

[3] Jotikasthira, Lundblad and Ramadorai (2012) argue that cash holdings do not seem to be an important determinant of portfolio allocations of funds subject to funding shocks. Coval and Stafford (2007) document that although funds experiencing extreme inflows hold more cash as funds are evaluated against all-equity benchmarks, few of them maintain significant cash balances.

decline.

The same mechanism works for managers with a good project opportunity subject to considerable underpricing. Because shareholders are pessimistic as a result of the lack of good projects and the lack of high returns in recent years, they believe that current projects will remain bad and therefore interpret the investment decision by the manager as a value-destroying one. The manager always decides not to invest and forgoes good investment opportunities.[4]

In the mechanism described above, at least four characteristics should be in place. First, the firm's assets should be opaque enough that the quality of the project does not become public too early. Second, mutual fund shareholders should have short-term liquidity needs so that they will sell their stocks before the quality of the project is revealed. Third, mutual fund shareholders under extreme flows should expand or reduce their current holdings in accordance with the flows from retail investors.

The catering mechanism described above can be empirically tested as follows:

Hypothesis 1: Corporate investment increases with stock mispricing driven by mutual fund extreme flows

The firm manager recognizes the price pressure coming from the mutual fund shareholders and invests according to the direction of retail investors' flows, especially if the flows are extreme.

The catering channel reflects inefficient decisions by the firm manager, i.e., a manager who executes value-destroying projects when the stock price pressure is high. Firms that make inefficient decisions should subsequently underperform, leading to the following additional empirical prediction:

[4]This chapter will focus on the overpricing/overinvestment rather than on the underpricing/underinvestment hypothesis test. The execution of a negative NPV project (which destroys value) by a firm that is overpriced and overinvests can be associated to lower stock returns. The lack of execution of a positive NPV project by a firm that is underpriced and underinvests does not necessarily lead to lower stock returns as the project can still be executed at a later moment.

Hypothesis 2: High price pressure firms that invest relatively much should subsequently underperform.

Firms with high lagged price pressure and high investment should have lower future returns and lower future operational performance. In particular, if we compare two firms with high price pressure, the firm that invests relatively more has lower future returns and lower future operational performance.

Hypothesis 1 contends that corporate investment increases with stock mispricing driven by mutual funds. This prediction might be consistent not only with the catering channel described above but also with alternative explanations that rely on external finance, such as the market timing channel explained by Baker et al. (2003). Firm managers of correctly priced and financially constrained firms should forgo positive net present value projects if a lack of financing exists. If the firm's stock becomes overpriced, the financial constraint is relaxed, the manager is able to issue extra equity or debt and the positive net present value project might proceed. To separate the catering and the market timing channels, it is important to study a subset of relatively financially unconstrained firms. This gives rise to the following empirical prediction:

Hypothesis 3: In a set of financially unconstrained firms, corporate investment should increase with stock price pressure driven by mutual fund extreme flows.

A subset of firms with relatively low financial constraints presents a significant investment reaction to lagged price pressure. For similar reasons, the same is true for a subset of firms that do not issue equity around the investment period.

Using the subsamples described above, I study the effects of lagged price pressure on firm investment in subsets of firms that do not need to raise external securities. In particular, I also study a subsample of firms that are not conducting SEOs around the investment period. Firm managers can still raise external securities when the firm does not need to seek external funding for their projects to arbitrage a high stock price. However, evidence consistent with a direct effect of price pressure on investment can be gathered if it is found that investment is still sensitive to stock price pressure when the firm does not issue equity.

Only firm managers with short-term incentives should react to high price pressure by investing more, even if the firm is not financially constrained. If shareholders have short-term horizons and do not know the quality of the project, the firm manager has more incentive to invest and, therefore, to boost the share price. For similar reasons, investment should be more sensitive to stock price pressure if the firm's assets are opaque because it takes shareholders longer to determine the quality of the project.

Hypothesis 4: Managers of firms with short-term shareholders should invest more than managers of firms with long-term shareholders. Managers of firms with more opaque assets should invest more than managers of firms with less opaque assets.

2.4 Data

2.4.1 Mutual Fund Data

U.S. mutual fund data come from the following 2 datasets : Thomson Financial CDA/Spectrum s12 for holdings data (CDA/s12) and CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP/MFDB), used for computing flow data. CDA/s12 provides quarterly holdings of U.S. mutual funds. CRSP/MFDB provides data on monthly total returns and monthly total net assets (TNA), used to infer mutual fund flows, and also contains extra information on the fund, including investment style and fee structure. I use the MFLINKS dataset to merge CDA/s12 and CRSP/MFDB. This method not only provides the identifiers to link the holdings and flow datasets but also enables the identification of single funds that are represented as different funds in CDA/s12 or CRSP/MFDB.[5] The final merged mutual fund dataset contains quarterly observations from 1991 to 2009.

The quarterly portfolio holdings provided by CDA/s12 are adjusted for corporate actions using the CRSP variable *cumulative factor to adjust shares/volume.* I run 4 filters to guarantee that the data are reliable. After passing filter 1, only fund months for which $0.5 < \frac{TNA_{f,t}}{TNA_{f,t-1}} < 3$ are kept to eliminate potential data errors. Filter 2 requires funds to be small enough at least for one period, i.e., $min_t(TNA_{f,t}) <$ US$ 1 Billion. Filter 3 compares TNAs from the merged datasets CDA/s12 and CRSP/MFDB. If the TNAs differ too much, the fund-month observation is eliminated (the fund-month observation is kept only if $\frac{1}{1.3} < \frac{TNA(CDA/s12)}{TNA(CRSP/MFDB)} < 1.3$). Finally, filter 4 guarantees that the dataset contains mostly domestic equity funds; all funds whose investment objective codes are international (ioc=1), municipal bonds (ioc=5), bonds and preferred (ioc=6) and metals (ioc=8) are eliminated.

Panel A of Table 2.1 describes the summary statistics of mutual funds' equity holdings after filters were passed. There are 4,717 unique mutual funds and 121,917 fund-quarter observations from the first quarter of 1991 to the second quarter of 2010. The median number of equity holdings per fund is relatively stable over the years, although the average increases considerably in the latter part of the sample.

[5]For instance, in CRSP/MFSB, there are funds that are offered as different share classes but that represent a single entity. In MFLINKS, those funds are assigned a unique identifier that I use to identify a single fund in the merged dataset. Similarly, some funds in CDA/s12 arbitrarily change names, although the fund remains the same; other groups of funds represent one single portfolio managed by one single person but offered under different fee structures and different names. MFLINKS allows those cases to be aggregated under one single fund.

In 2009, a fund held, on average, 148.7 equity holdings in its portfolio. The same pattern applies to the dollar value of the fund equity holdings. In 2009, a fund held, on average US$ 1.26 billion, in U.S. stocks. The number of stocks held by at least one mutual fund fluctuates between 5,000 and 7,000. Finally, it is relevant that the proportion of the dollar value of U.S. stocks held by all mutual funds in the dataset increases considerably over the years and is 12.93% in 2009.

2.4.2 Fund Flows

The monthly net flows into mutual funds are computed using TNAs and monthly net returns from CRSP/MFDB. Borrowing from the mutual fund literature, monthly flows are computed in the following way:

$$FLOW_{f,t} = TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})$$
$$flow_{f,t} = \frac{FLOW_{f,t}}{TNA_{f,t-1}}$$

FLOW represents the net dollar value that retail investors deposit in a mutual fund during a month, whereas flow is the proportion of FLOW as the beginning-of-month TNA.

The fund flow data are described in Panel B of Table 2.1. The 3-month and 6-month cumulative proportionate flows are highly correlated, and the latter flow shows a wider distribution than the former, illustrating the consequences of the known persistence of fund flows. The growth in the mutual fund industry can be ascertained by the fact that in most years, the mean of fund flows is significantly positive; only in 2008 and 2009 were the fund flows' means negative. Another striking feature of fund flows is their positive skewness; that is, the 90^{th} percentile is higher than the absolute value of the 10^{th} percentile.

2.4.3 Other Data

Accounting data such as earnings, book value of assets and capital expenditure come from Compustat North America, which provides annual data on active and inactive U.S. publicly held companies from income statements, balance sheets, statement of cash flows, and other supplemental sources. Financial and utilities firms and firms whose total assets are less than US$ 10 million are excluded from the dataset.

The merged mutual fund flow and holdings dataset CDA/s12 - CRSP/MFDB is intersected with Compustat, and the final dataset contains annual data from 1992 to 2010. The summary statistics can be found in Table 2.2. To exclude data errors and odd outliers, all variables are Winsorized at the 1% level.

Finally, data on U.S. seasoned equity offerings come from Thomson Securities Data Center. Stock prices and stock returns data come from the CRSP U.S. stock database. Both datasets are linked to the CDA/s12 - CRSP/MFDB - Compustat merged datasets using the unique stock identifier CUSIP.

2.4.4 Stock Price Pressure

I employ a flow-related measure at the stock level, as in Coval and Stafford (2007), to measure shifts in stock demand. Mutual funds, which own a significant aggregate amount of holdings of U.S. firms, are liquid institutional investors that generally do not hold a considerable amount of cash for regulatory or market reasons. In turn, when faced with relevant outflows (inflows) from their retail investors, their main reaction is to reduce (expand) their existing equity holdings. This leads to non-fundamental shocks in the stock demand. Furthermore, this effect can be amplified if a stock is held by many funds under extreme flows, as described in Anton and Polk (2010) and Greenwood and Thesmar (2011).

The price pressure measure is constructed at the stock-period level and reflects flows over the previous 12 months. This measure is built in the following two stages:

(i) first, a quarterly measure is calculated to assess the number of purchases by funds under extreme flows, netted out of the number of sales by funds under extreme outflows as a proportion of total shares outstanding; (ii) second, an annual price pressure measure is computed by averaging the quarterly measure over the previous 4 quarters.

First stage:

$$PP^{3m}_{s,t} = \frac{\sum_f max(0, \Delta holdings_{f,s,t} | flow_{f,t-3:t} \geq 90^{th}\text{p})}{\text{shares} \quad \text{outstanding}_{s,t-1}} + \\ - \frac{\sum_f max(0, -\Delta holdings_{f,s,t} | flow_{f,t-3:t} \leq 10^{th}\text{p})}{\text{shares} \quad \text{outstanding}_{s,t-1}}$$

Second stage:

$$PP_{s,t} = \frac{PP^{3m}_{s,t} + PP^{3m}_{s,t-3} + PP^{3m}_{s,t-6} + PP^{3m}_{s,t-9}}{4}$$

in which $\Delta holdings_{f,s,t} = holdings_{f,s,t} - holdings_{f,s,t-3}$ is the change in fund f's holdings of stocks over the past 3 months; $flow_{f,t-3:t}$ is the cumulative monthly flows into fund f over the past 3 months; and $shares\ outstanding_{s,t-1}$ is the total shares outstanding in month t-1.

I test whether the price pressure measure is consistent with a reversal pattern in stock prices. I run calendar-time portfolio regressions in which a zero-cost portfolio, long in the top and short in the bottom decile of all U.S. stock quarters, is formed. More precisely, in March, June, September and December of each year t, U.S. stocks are sorted according to the price pressure variable. The equal-weighted and value-weighted average returns of the *high price pressure* top decile portfolio and the *low price pressure* bottom decile portfolio are calculated. For December of year t and January and February of year t+1, the strategy buys the *high price pressure* portfolio and sells the *low price pressure* portfolio formed in December of year t. For September, October and November of year t, the strategy buys the *high price pressure* portfolio and sells the *low price pressure* portfolio formed in September of year t. For June, July and August of year t, the strategy buys the *high price pressure* portfolio and sells the *low price pressure* portfolio formed in June of year t. For March, April and May of year t, the strategy buys the *high price pressure* portfolio and sells the *low price pressure* portfolio formed in March of year t. Returns using this strategy are computed for various holdings periods, one for each row of Table 2.3. Equal-weighted returns of overlapping portfolios for different holding periods are computed. Finally, the dependent variable is the excess return, which is equal to the overlapping portfolio return minus the U.S. risk-free rate. Four different specifications are run, controlling for the following sets of risk factors: (i) no risk factors; (ii) only the market factor (MKT); (iii) the factors market (MKT), size (SMB) and value (HML); and (iv) the factors market (MKT), size (SMB), value (HML) and momentum (UMD).

$$R_{PP,t} - R_{f,t} = \alpha + \epsilon_t$$

$$R_{PP,t} - R_{f,t} = \alpha + \beta_1(R_{M,t} - R_{f,t}) + \epsilon_t$$

$$R_{PP,t} - R_{f,t} = \alpha + \beta_1(R_{M,t} - R_{f,t}) + \beta_2 R_{SMB,t} + \beta_3 R_{HML,t} + \epsilon_t$$

$$R_{PP,t} - R_{f,t} = \alpha + \beta_1(R_{M,t} - R_{f,t}) + \beta_2 R_{SMB,t} + \beta_3 R_{HML,t} + \beta_4 R_{UMD,t} + \epsilon_t$$

The calendar-time portfolio return results are consistent with a reversal pattern associated with stock price pressure. In Table 3, the estimated intercept α coefficients are reported. As expected, the portfolios long in high price pressure and short in low price pressure are linked to future significant negative returns. For the equally weighted portfolios held from quarter 5 to 12 after the portfolio formation, excess monthly returns are -0.74% (-0.62% when controlled for 3 risk factors and -0.58% when controlled for 4 risk factors). For value-weighted portfolios, the returns are slightly lower in absolute value, in line with the fact that mutual funds concentrate their portfolios in large liquid stocks. For the holding period from quarter 5 to 12 after the portfolio formation, the value-weighted portfolio excess monthly returns are -0.63% (-0.60% when controlled for 3 risk factors and -0.56% when controlled for 4 risk factors).

2.5 Results

2.5.1 Corporate Investment and Price Pressure

Having shown that the price pressure variable is consistent with a return reversal pattern, I proceed to investigate whether this finding affects future corporate investment policy. Controlling for other determinants of investment policy, including Tobin's Q, cash flow, cash from equity issuance and past stock returns, I run the following specification:

$$\frac{I_{s,t}}{K_{s,t-12}} = f_s + y_t + \beta_1 PP_{s,t-12} + \beta_2 Q_{s,t-12} + \beta_3 \frac{CF_{s,t-12}}{K_{s,t-24}} + \beta_4 \frac{E_{s,t}}{K_{s,t-12}} + \\ + \beta_5 R_{s,t-13:t-12} + \beta_6 R_{s,t-24:t-13} + \beta_7 R_{s,t-72:t-24} + \epsilon_{s,t}$$

The dependent variable is investment (capital expenditure) as a proportion of beginning-of-year capital (net property, plant and equipment). The main regressor is the lagged price pressure variable, which uses the change in holdings and flows between lags of 12 and 24 months. Because only firms with fiscal year-end months in December are included, there is no overlap between the investment period[6] and the period over which the price pressure variable is measured.

To control for the fact that firms might be investing more as a result of more available investment opportunities, the lagged marginal Tobin's Q ratio is proxied by the lagged average Q ratio, which is defined as the market value of assets[7] divided by the book value of assets. Much evidence is found in the literature that firms that have a higher net worth invest more. To control for this effect, lagged cash flow as a proportion of beginning-of-year capital, which equals the sum of earnings before extraordinary items and depreciation over beginning-of-year capital, is included as a control. Because I am interested in identifying an investment channel that is independent of external financing, I also control for cash from equity issuance.

[6] The investment period is between months t-12 and t.

[7] A firm's market value of assets equals the book value of assets plus the market value of common stock less the sum of book value of common stock and balance sheet deferred taxes.

One concern is that the price pressure variable might contain information on the fundamentals of the firm. To address this issue, I include past stock returns from month t-72 until month t-12 as additional regressors. Under this approach, the coefficient on the price pressure variable is orthogonal to past stock returns and becomes a better proxy for the effect of stock uninformative demand on firm investment.

In addition, firm fixed effects and year effects are also used, and standard errors are clustered at the firm level. Finally, all firm-years for which the aggregate mutual fund ownership in the dataset is lower than 1% are excluded.

The results shown in Table 3.3 confirm that lagged priced pressure positively and significantly influences corporate investment. In the specification with lagged price pressure, including Tobin's Q, cash flow and cash from equity issuance, the main coefficient of investment on lagged price pressure is 5.285 (t=4.17). This effect is economically important; an increase of one standard deviation in the lagged price pressure variable leads to an increase in investment as a proportion of lagged capital of 1.84%, which corresponds to 2.30% standard deviations and 8.33% of the median of the same variable. Across all specifications, the main coefficient is positive and significant at the 1% level. The specification that also includes past stock returns has an estimated coefficient of the investment sensitivity to lagged price pressure of 3.680 (t=2.79). The effect remains economically important; an increase of one standard deviation in the lagged price pressure variable leads to an increase in investment as a proportion of lagged capital of 1.28%, which corresponds to 1.60% standard deviations and 5.80% of the median of the same variable.

2.5.2 High Price Pressure, High Investment and Lower Future Performance

Because lagged stock price pressure is positively related to future firm investment, it is reasonable to investigate the channel through which the uninformative component of stock prices influences a firm manager's decision to invest. If high price pressure allows the firm manager to finance value-enhancing projects that previously lacked funding, the decision to adopt the investment project increases the firm's future performance. In contrast, if high price pressure leads the firm manager to execute a value-destroying project, the decision to adopt the investment project decreases the firm's future performance[8].

Since lagged stock price pressure is positive related to future firm investment, it is natural to investigate through which channel the uninformative component of stock prices influences the firm manager decision to invest. If high price pressure allows the firm manager to finance value-enhancing projects that previously lacked funding, the decision to execute the investment project increases the firm's future performance. In contrast, if high price pressure leads the firm manager to execute value-destroying project, the decision to execute the investment project decreases the firm's future performance[9].

It is particularly challenging to identify through future performance whether high price pressure leads the firm manager to execute either value-enhancing or value-destroying projects. The reason is that high price pressure predicts future lower returns. I address this concern in the following two ways: (i) I run Fama and MacBeth (1973) regressions with future monthly stock returns as the dependent variable and study the interaction between firm investment and price pressure; (ii) I also investigate the effect of investment and price pressure on operational performance and run pooled OLS regressions with the change in return on assets as the dependent variable.

First, I use future monthly stock returns from 6 until 18 months after the end

[8] While it is clear that the execution of value-destroying projects should lead to future firm underperformance, the effects of the non-execution of value-enhancing projects are less clear. Unless those projects are once in a lifetime opportunities and can only be executed at a specific time, firms could wait for a better timing to execute the project.

[9] Although it is clear that the execution of value-destroying projects should lead to future firm underperformance, the effects of the non-execution of value-enhancing projects are less clear. Unless those projects are once-in-a-lifetime opportunities and can only be executed at a specific time, firms could wait for better timing to execute the project.

of the investment period as the dependent variable in Fama and MacBeth (1973) regressions.[10] The main regressors are the log of current investment over lagged capital, the lagged stock price pressure and their interaction. I also use as controls the log of Tobin's Q, cash flow as a ratio of lagged capital, momentum[11], and their interaction with lagged price pressure.

$$\begin{aligned}R_{s,t+6,t+18} =&\beta_1 ln(\frac{I_{s,t}}{K_{s,t-12}}) + \beta_2 PP_{s,t-12} + \beta_3 PP_{s,t-12} * ln(\frac{I_{s,t}}{K_{s,t-12}})+\\&+\beta_4 ln(Q_{s,t}) + \beta_5 \frac{CF_{s,t}}{K_{s,t-12}} + \beta_6 MoM_t + \beta_7 PP_{s,t-12} * ln(Q_{s,t})+\\&+\beta_8 PP_{s,t-12} * \frac{CF_{s,t}}{K_{s,t-12}} + \beta_9 PP_{s,t-12} * MoM_t + \epsilon_{s,t}\end{aligned}$$

Consistent with firm managers' execution of value-destroying projects, in Table 2.5, I find an estimated coefficient of the interaction between investment and price pressure β_3 of -0.428 (t=-3.12). One possible interpretation is that a firm with high price pressure that invests more than another firm with an equally high price pressure has lower future returns[12]. This result suggests that firms with high price pressure that invest too much are destroying value and, thus, are executing negative net present value projects.

I also confirm previous results found in the literature that firms that invest too much have lower future stock returns, as shown in Titman, Wei and Xie (2004) and Polk and Sapienza (2009). The coefficient of future stock returns on current log investment over lagged capital is negative, stable across specifications and significant at the 1% level for most specifications. The coefficient on lagged price pressure is also negative and significant, in line with the reversal pattern documented in Section 2.5.

Second, I test future firm performance by using an accounting variable rather than

[10] The methodology consists of two stages. In the first stage, cross-sectional OLS estimates are run for each period. In the second stage, the estimated coefficients means and standard errors, which are shown in Table 2.5, are computed.

[11] Momentum is defined as the cumulative past stock abnormal return from month t-12 to month t-1.

[12] It is a concern that the regressor is actual investment and not the surprise in investment. I assume that firms that invest more had higher expected investment.

a market-based variable. I run pooled OLS regressions with the change in return on assets as the dependent variable. Return on assets (ROA) is defined as operating income before depreciation as a proportion of beginning-of-year assets. I use ROA in year 1 minus current ROA as the measure of future firm performance.

$$\begin{aligned}\Delta(ROA)_{t,t+12} =& \beta_1 ln(\frac{I_{s,t}}{K_{s,t-12}}) + \beta_2 PP_{s,t-12} + \beta_3 PP_{s,t-12} * ln(\frac{I_{s,t}}{K_{s,t-12}}) + \\ &+ \beta_4 ln(Q_{s,t}) + \beta_5 \frac{CF_{s,t}}{K_{s,t-12}} + \beta_6 MoM_t + \beta_7 PP_{s,t-12} * ln(Q_{s,t}) + \\ &+ \beta_8 PP_{s,t-12} * \frac{CF_{s,t}}{K_{s,t-12}} + \beta_9 PP_{s,t-12} * MoM_t + \epsilon_{s,t}\end{aligned}$$

Results in Table 2.6 indicate that firms with high price pressure and high investment have lower future operational performance. The main coefficient of the interaction between investment and price pressure has always a negative point estimate and is significant for 2 specifications when industry fixed effects are used. The coefficients on investment and on price pressure are always negative and in most specifications significant, suggesting high-price-pressure firms and high-investment firms have lower future operational performance.

Together, the future performance regressions indicate there is a direct effect of stock price pressure on the execution of negative net present value projects.

2.5.3 Firm Investment when External Finance is Not Needed

In this section, I provide evidence of a link between stock price pressure and firm investment that does not rely on external finance. I show that the investment sensitivity to lagged price pressure remains economically and significantly positive to a subset of firms that are relatively financially unconstrained, according to the following 2 indices of financial constraints: (i) the Kaplan and Zingales (1997) KZ index, built by Lamont, Polk and Saa-Requejo (2001); and (ii) the Hadlock and Pierce (2010) size-age SA index. To complement the study on the direct influence of high stock price pressure on firm investment, I also investigate a subset of firms that do not issue equity around the investment period and find that the investment sensitivity to stock price pressure is still positive and significant.

Financially Unconstrained Firms

In Table 2.7, I split the sample into the following 2 subsets: (i) *High KZ*, for relatively financially constrained firm years, or those whose KZ index is above the KZ median in the same year; (ii) *Low KZ*, for relatively financially unconstrained firm years, or those whose KZ index is below the KZ median in the same year. The KZ index of financial constraint is as follows:

$$KZ_t = -1.001909\frac{CF_t}{K_{t-1}} + 0.2826389Q_t + 3.139193\frac{debt_t}{debt_t + equity_t} + \\ -39.3678\frac{div_t}{K_{t-1}} - 1.314759\frac{Cash_t}{K_{t-1}}$$

A firm is more financially constrained in year t if its Tobin's Q and its book leverage ($Lev_t = \frac{debt_t}{debt_t+equity_t}$) are higher and if its cash flow, dividends and cash balance as a ratio of beginning of the year capital are lower.

The results indicate that there is an operating investment channel for the *Low KZ* group of relatively financially unconstrained firms. The investment sensitivity of lagged price pressure has a coefficient of 5.451 (t=2.08) in the specification that includes all past stock returns. This finding has economic relevance; an increase of one standard deviation in lagged price pressure leads to an increase of 1.90% in investment over lagged capital. Notably, across all specifications, the point-estimate coefficient for the *High KZ* group of relatively financially constrained firms is lower than the point-estimate coefficient for the *Low KZ* group of relatively financially unconstrained firms.

In Table 2.8, I implement a similar test but now use the SA index of financial constraints, which has a low correlation with the KZ index given that they do not have any common components:

$$SA_t = -0.737ln(Size_t) + 0.043[ln(Size_t)]^2 - 0.040Age_t$$

in which Size is equal to total assets and is capped at ln (US$ 4.5 billion). Age is capped at 37. The higher the SA index, i.e., the smaller and the younger the firm, the more financially constrained is the firm.

In a similar way, I split the sample into a subset of *High SA*, relatively financially constrained firms and *Low SA*, relatively financially unconstrained firms. The *Low SA* specification that includes all past stock returns has a coefficient of 2.834 (t=2.59). An increase of one standard deviation in the lagged price pressure is equivalent to an increase of 0.99% of investment over lagged capital. The coefficient of the *High SA*, relatively financially constrained firms is always positive but is not significant at the 10% level across all specifications.

Firms that Do Not Conduct SEOs

The results above demonstrate that high stock price pressure predicts future investment in relatively financially unconstrained firms, suggesting a working investment channel that operates independently of external finance. Although firms with plentiful internal funds can still raise external securities when there is high stock price pressure[13], it is worth investigating whether high stock price pressure can still explain future investment even for firms that do not seek to raise external securities.

In Table 2.9, I exclude all firms that went through at least one seasoned equity offering in the investment year and in the year preceding the investment year. I identify firms that have an SEO in a year using the Thomson Securities Data Center dataset. Table 2.14 presents summary statistics for SEOs by year. I then intersect the SEO data with the merged firm-year-level dataset and exclude from the sample all

[13] Loughran and Ritter (1995) show that firms conducting initial public offerings or seasoned equity offerings underperform non-issuing firms during the 5 years after the offering date.

firms that went through at least 1 SEO in the current and previous years. Lagged price pressure remains positive and significantly predicts investment. The coefficient in the specification with all past returns as regressors is 3.232 (t=2.25), which corresponds to a 1 standard deviation increase in the lagged price pressure having an effect of increasing in 1.12% investment over lagged capital. This finding provides additional evidence of a direct channel of stock mispricing influencing future firm investment.

2.5.4 Short-Term Horizon Shareholders

Models from Stein (1996) and Polk and Sapienza (2009) predict that firm managers cater more if shareholders have a shorter horizon. If there is high price pressure from mutual fund flows and the firm manager executes a negative net present value project, shareholders will profit from the temporary stock overpricing only if they sell their holdings before it becomes publicly known that the project was value-destroying. Anticipating that, the firm manager will only proceed with the negative net present value project if shareholders have a short enough horizon.

To test this prediction, I use mutual fund churn rates projected at the stock level as a proxy for shareholders' horizons. Firms whose mutual fund shareholders churn often, i.e., frequently trade their holdings, are considered firms with a short-term horizon. To build a proxy for short-term horizons at the firm-year level, two steps are employed. In the first step, the churn rate at the fund-quarter level is built. Borrowing from Gaspar, Massa and Matos (2005), churn rate at the fund level is depicted by the following:

$$CR_{f,t} = 2\frac{\sum_{s\in S} \mid (N_{f,s,t} - N_{f,s,t-3})P_{s,t} \mid}{\sum_{s\in S} N_{f,s,t}P_{s,t} + N_{f,s,t-3}P_{s,t-3}}$$

where $N_{f,s,t}$ is the number of shares held in firm s by mutual fund f in period t and $P_{s,t}$ is the share price in dollars of firm s in period t. Mutual funds that churn more are considered having a shorter-term horizon.

To assess a firm's horizon, the churn rate at the stock-quarter level is built by projecting mutual fund churn rates at the stock level and averaging them over 4 consecutive quarters as follows.

$$CR_{s,t} = \sum_{f \in F} \omega_{s,f,t} \frac{1}{4}(CR_{f,t} + CR_{f,t-3} + CR_{f,t-6} + CR_{f,t-9})$$

where $\omega_{s,f,t}$ is the proportion of shares of mutual fund f in firm s in quarter t with respect to total shares outstanding of firm s in period t. The churn ratio at the stock-year level is a fund-weighted average of the churn rate at the fund-quarter level of the last four quarters. A high (low) stock-year churn rate indicates a short-term (long-term) mutual fund shareholder.

In Table 2.10, I sort firms according to last year's churn rate at the stock level $CR_{s,t-12}$. A *Low CR* represents long-horizon shareholders, or those in the bottom 3 deciles of last year's churn rate. A *High CR* represents short-horizon shareholders, or those in the top 3 deciles of last year's churn rate.

The results are in line with the catering model cross-sectional predictions. The main coefficients of investment on lagged price pressure in the subsamples with high churn rates are higher than the subsamples with low churn rates across all specifications. In the specification without past stock returns as regressors, the coefficient on *High CR* is 8.085 (t=2.58) and the coefficient on *Low CR* is 1.195 (t=0.54). In the specification with all past stock returns as regressors, the coefficient on *High CR* is 6.535 (t=2.01) and the coefficient on *Low CR* is 3.565 (t=1.57). Those estimates are consistent with a firm manager with steeper incentives to maximize the current stock price reacting more strongly to high price pressure when investing.

2.5.5 Firms with More Opaque Assets

If shareholders cannot easily ascertain how the firm's invested projects are faring, they will place a higher importance on simple sets of information such as how much rather than how well the firm is investing. In firms with opaque assets, such as those in the IT or pharmaceutical industries, it takes much longer for shareholders to find out how the projects currently being initiated will perform. The lack of transparency in a firm's assets creates catering incentives for firm managers, who more easily engage in value-destroying projects if there is high stock price pressure and a lack of good projects.

In Table 2.11, I test whether the investment sensitivity to stock price pressure is higher for firms with more opaque assets. I proxy asset opaqueness by R&D intensity, defined as research and development expenses as a proportion of beginning-of-the-year assets[14].

Firm-years for which last year's R&D intensity are above the median of last year's R&D intensity for all firms are considered to be firms with more opaque assets, in which case catering should be stronger. The coefficient estimates are as expected. The subsamples with *High R&D* intensity have high positive investment-lagged price pressure coefficients significant at the 1% level. In the specification without past stock returns as controls, the *High R&D* coefficient is 8.141 (t=2.51), higher than the *Low R&D* coefficient 4.633 (t=2.10). The inclusion of past stock returns as controls does not seem to change the main result. The *High R&D* coefficient is 7.520 (t=1.94), still higher than the *Low R&D* coefficient 2.267 (t=1.30).

2.6 Robustness Tests

2.6.1 Measurement Error in Q

It is concerning that one of the regressors, the proxy for investment opportunities, is the observable average Q rather than the unobservable marginal Q. If the price pressure variable contains information about investment opportunities and marginal Q is not properly measured, the interpretation of results might be compromised.

[14]The use of R&D intensity as a proxy of opaqueness is supported by Aboody and Lev (2000), who show that insider gains in firms with R&D are considerably larger than in firms without R&D.

To handle this errors-in-variables problem, I use Erickson and Whited (2002) and Erickson and Whited (2000)'s methodology, which exploits higher-order moments equations that produce a measurement error consistent GMM estimator for the effect of Q on investment. I run Tim Erickson and Toni Whited's Stata code for unbalanced panels, which executes the identification diagnostic tests and computes the estimators.

Results in Table 2.12 show that the estimates in the specification without fixed effects for the lagged price pressure variable's effect on investment remain economically and statistically significant for the higher moments estimators, which reassures us that the results are not undermined by the measurement error problem.

2.6.2 Price Pressure Variables

In this subsection, I show that the results are robust for the definition of the price pressure variable. Until now, I have been using the price pressure variable defined in Equation2.4.4. Below, I define 3 slightly different versions of the price pressure variable, which are borrowed from Coval and Stafford (2007) (PP2 and PP3) and from Gao and Lou (2011) (PP4):

$$
\begin{aligned}
PP2^{3m}_{s,t} &= \frac{\sum_f max(0, \Delta holdings_{f,s,t}) \times max(0, flow_{f,t-3:t})}{\text{Volume}_{s,t-12:t-6}} \\
&- \frac{\sum_f max(0, -\Delta holdings_{f,s,t}) \times max(0, -flow_{f,t-3:t})}{\text{Volume}_{s,t-12:t-6}} \\
PP3^{3m}_{s,t} &= \frac{\sum_f max(0, \Delta holdings_{f,s,t} | flow_{f,t-3:t} \geq 90^{th}\text{p})}{\text{Volume}_{s,t-12:t-6}} \\
&- \frac{\sum_f max(0, -\Delta holdings_{f,s,t} | flow_{f,t-3:t} \leq 10^{th}\text{p})}{\text{Volume}_{s,t-12:t-6}} \\
PP4^{3m}_{s,t} &= \frac{\sum_f [flow_{f,t-3:t} \times holdings_{f,s,t-3}]}{\sum_f holdings_{f,s,t-3}}
\end{aligned}
$$

in which $\Delta holdings_{f,s,t} = holdings_{f,s,t} - holdings_{f,s,t-3}$ is the change in fund f's holdings of stock s over the past 3 months; $flow_{f,t-3:t}$ is the cumulative monthly flows into fund f over the past 3 months; and $Volume_{s,t-12:t-6}$ is the total stock cumulated volume traded in number of shares from months t-12 to month t-6.

Finally, all quarterly price pressure variables are averaged as the original one to reflect the past 12 months' flows:

$$PPk_{s,t} = \frac{PPk^{3m}_{s,t} + PPk^{3m}_{s,t-3} + PPk^{3m}_{s,t-6} + PPk^{3m}_{s,t-9}}{4}$$

PP2 and PP4 take into account flows from all funds, unlike PP and PP3, which only reflect extreme flows. The difference between PP2 and PP4 is stark; whereas PP2 takes into account purchases (sales) from funds with positive (negative) flows scaled by the total cumulated volume traded between months t-12 and t-6, PP4 emphasizes the flows rather than stock trades and only uses the holdings of funds as weights when aggregating the flows of all funds that have holdings in the stock s. In contrast, the difference between PP and PP3 is quite subtle; whereas the latter uses the total cumulated volume traded between months t-12 and t-6, the former uses the total number of shares outstanding in month t-1 as a denominator.

I then rerun the same regressions run in Table 3.3 and present the results in Table 2.13. Each row corresponds to a different price pressure variable and each column to a different specification that includes different past stock return controls. I omit the control coefficients estimates for the sake of highlighting the main investment-price-pressure coefficient. Notably, almost all estimates are positive, and many are significant.

In terms of economic significance, there is also resemblance to the original PP variable. An increase of one standard deviation in PP, PP2, PP3 and PP4 has an effect of, respectively, increasing 1.60%, 0.97%, 1.14% and 0.31% standard deviations of the investment over lagged capital variable, which represents 5.80%, 3.53%, 4.14% and 1.12% of the median of the same variable.

2.7 Conclusion

This chapter provides evidence that relatively financially unconstrained firms might react to high stock price pressure from mutual funds by investing in negative net present value projects, catering to short-term shareholders who expect that the firm presents good investment opportunities. By investing, the firm manager aims to increase the stock price in the near term and hopes that the short-term shareholders will sell their stakes in the firm before knowledge becomes public that the project was value-destroying.

Natural extensions of the analysis might include studying how some firm managers' characteristics, such as horizon, degree of overconfidence/optimism and share of the total firm's shares outstanding, might affect the catering mechanism. One reason why firm managers try to maximize the wealth of the average current shareholder rather than the long-term value of the firm is that, in general, current shareholders have the power to fire a firm manager if they are not satisfied with her actions. One possible point of contention is the possibility that the investment policy and the catering incentive might reflect a firm with powerful shareholders and a less powerful firm manager. In contrast, if the firm manager is a family founder or an important stakeholder in the firm, I expect the catering mechanism to be weaker because the firm manager can focus on a longer-horizon objective for her actions. Of course, this is the same reason underlying the fact that a firm manager with shorter horizon should cater more. Perhaps a more interesting analysis is the interaction of the catering effects with proxies for a firm manager's overconfidence and optimism. On the one hand, such a firm manager should invest more than if she were not overconfident/optimistic because she believes stock returns are higher than they actually are or that stock returns are less volatile than they actually are. That finding would be consistent with more overinvestment for overpriced firms and less underinvestment for underpriced firms. On the other hand, an overconfident/optimistic manager should not care as much about what shareholders think and should pay less attention to price pressure proxies. Investigations on the above-mentioned trade-off and on the interaction between catering with firm manager overconfidence/optimism are worthy of future study.

Figure 2.1: **Cumulated Returns on an High Price Pressure Portfolio.** The figure shows the cumulated return of a portfolio long in high and short in low price pressure stocks.

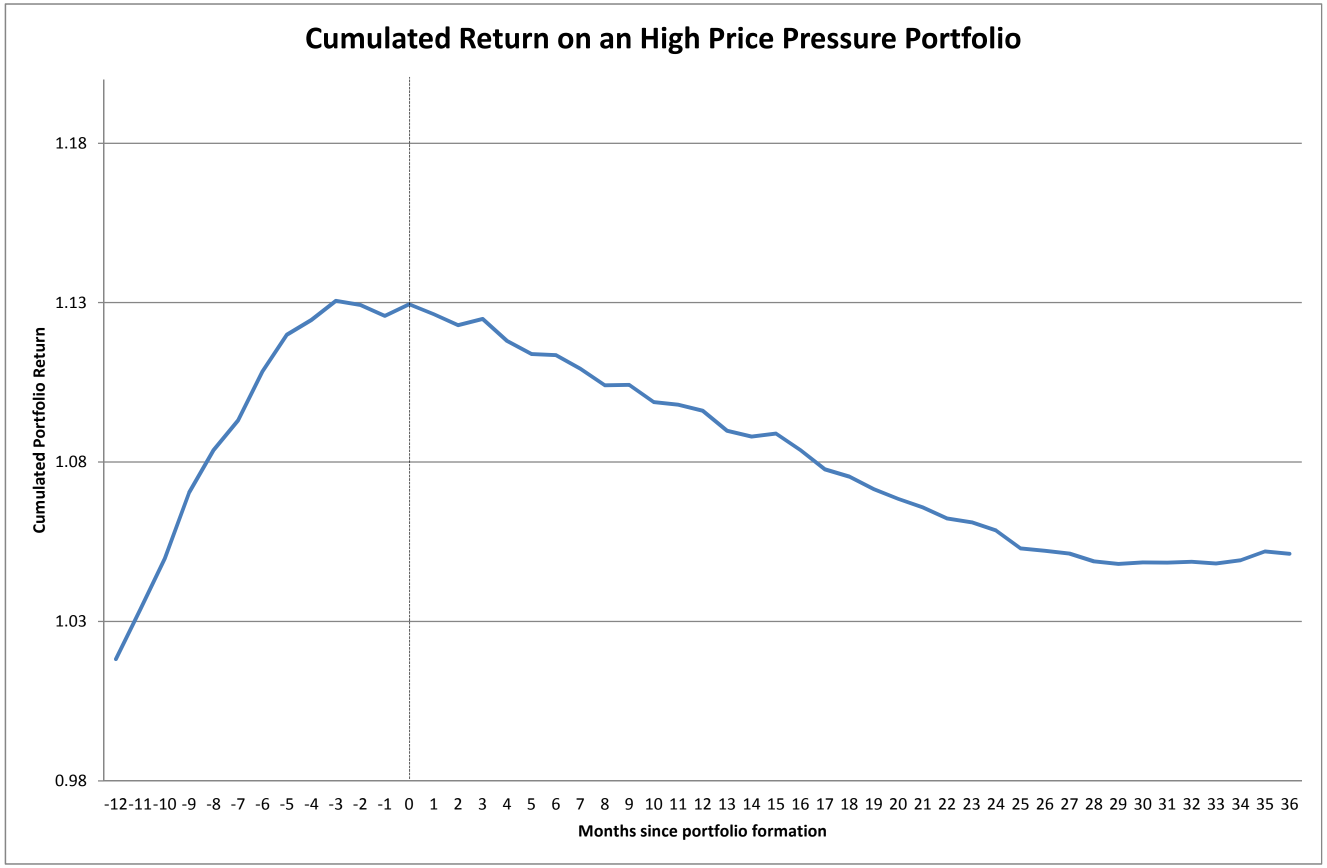


Table 2.1: **Mutual Fund Summary Statistics**

This table reports end-of the-year US equity domestic mutual fund variables from 1991 to 2009. The sample below is the intersection of the mutual fund equity holdings *Thomson CDA/s12* and the survivor bias free *CRSP/MFDB* datasets. The merging used the identifier provided by the database *MFLinks*. A number of funds were excluded in order to guarantee the reliability of the data. For more details, see description of filter in Section 2.4. Panel A describes equity holdings variables at the fund level. *Number of funds* is the number of mutual funds at the end of the year. *Number of equity holdings per fund* is the number of stock holdings held by each fund at the end of the year. *US$ Million equity holdings per fund* is the total dollar value of all equity holdings held by a fund at the end of the year. *Number of stocks* is the number of US stocks that are held by at least one mutual fund at the end of the year. *Number of fund-stocks* is the aggregate number of stock holdings by all funds at the end of the year. *US equity market share* is the dollar proportion of US stocks held by all mutual funds in the dataset at the end of the year. Panel B describes flow variables at the fund level. *TNA (US$ Million)* is the Total Net Assets per fund as reported in the *CRSP/MFDB* dataset. *flow t:t-3* is the cumulative fund flow in the last quarter. *flow t:t-6* is the cumulative fund flow in the last 2 quarters. The monthly fund flow is defined as $\frac{TNA_t - TNA_{t-1}(Fund\_Return_t)}{TNA_{t-1}}$.

Panel A: Equity Holdings characteristics per fund

Year	**Number of funds**	**Number of equity holdings per fund**		**US$ Million equity holdings per fund**		**Number of stocks**	**Number of fund-stocks**	**US equity market share**
		Mean	Median	Mean	Median			
1991	605	75.6	49.0	302.4	74.1	4062	45768	4.58%
1992	660	89.1	54.0	401.9	98.9	4248	58803	6.03%
1993	771	100.1	55.0	379.8	82.3	5681	77201	5.79%
1994	882	96.8	54.5	360.1	72.4	6152	85396	6.35%
1995	887	99.9	56.0	498.7	93.8	6435	88569	6.52%
1996	1142	98.8	61.0	563.9	96.2	6591	112808	7.76%
1997	1225	99.0	59.0	735.3	108.7	7081	121280	8.35%
1998	1422	100.2	57.5	844.5	113.4	6840	142441	9.04%
1999	1747	110.6	63.0	949.7	122.4	6923	193204	9.76%
2000	1865	110.3	60.0	875.7	128.0	7156	205645	10.49%
2001	1852	118.4	62.0	667.9	105.0	6658	219236	8.95%
2002	2014	127.0	64.0	619.7	85.7	5901	255799	11.32%
2003	2222	132.6	68.0	784.4	107.7	6245	294660	11.96%
2004	2383	126.4	65.0	933.4	131.0	5638	301219	13.52%
2005	2176	129.6	65.0	1143.0	147.1	6235	281968	14.32%
2006	2348	123.8	64.0	1266.4	166.9	6182	290615	15.22%
2007	2333	125.4	61.0	1322.2	171.9	6471	292637	15.55%
2008	2092	129.5	62.0	773.3	126.0	6174	270972	13.82%
2009	1548	148.7	75.5	1257.4	239.9	5510	230189	12.93%

Table 2.1: **Mutual Fund Summary Statistics(cont.)**

Panel B: Flow characteristics per fund

Year	**TNA (US$ Million)**		**flow t:t-3**				**flow t:t-6**			
	Mean	Median	$10^{th} Pctile$	Mean	Median	$90^{th} Pctile$	$10^{th} Pctile$	Mean	Median	$90^{th} Pctile$
1991	409.1	102.9	-6.42%	5.22%	0.99%	19.94%	-12.14%	11.86%	1.22%	38.67%
1992	558.1	144.8	-5.23%	8.44%	2.30%	24.57%	-8.49%	12.04%	3.96%	40.40%
1993	561.0	128.8	-6.41%	6.35%	2.38%	22.37%	-10.81%	17.37%	4.95%	51.86%
1994	550.2	112.8	-7.41%	3.37%	-0.02%	13.25%	-12.32%	8.00%	0.74%	31.97%
1995	758.8	140.9	-6.66%	3.76%	0.79%	16.78%	-9.75%	13.75%	2.85%	42.20%
1996	790.1	134.3	-8.10%	5.67%	0.52%	19.00%	-11.93%	13.62%	1.73%	39.85%
1997	1048.2	170.7	-6.10%	5.91%	1.22%	19.61%	-9.64%	19.20%	3.38%	50.62%
1998	1131.5	162.6	-10.24%	2.26%	-1.28%	13.96%	-14.26%	6.18%	-1.35%	26.06%
1999	1172.1	176.4	-12.01%	4.49%	-1.93%	20.63%	-16.80%	8.72%	-2.27%	37.35%
2000	1125.6	185.1	-7.10%	4.68%	-0.46%	16.51%	-12.81%	10.96%	0.01%	37.33%
2001	846.5	144.6	-7.29%	5.05%	-0.27%	21.20%	-11.27%	7.20%	-1.05%	29.05%
2002	793.8	125.0	-8.15%	2.05%	-1.29%	14.29%	-13.95%	3.02%	-3.44%	22.65%
2003	1015.2	162.4	-7.86%	5.61%	0.71%	22.09%	-11.98%	13.60%	2.02%	47.07%
2004	1242.1	195.9	-9.07%	3.15%	-0.98%	16.68%	-14.01%	6.13%	-1.51%	29.60%
2005	1473.4	210.6	-7.87%	4.10%	-0.71%	17.38%	-15.11%	10.26%	-1.37%	41.40%
2006	1677.4	261.7	-9.81%	0.56%	-1.83%	12.81%	-16.31%	2.91%	-3.38%	29.87%
2007	1813.1	285.7	-10.33%	0.09%	-1.84%	10.46%	-15.64%	2.56%	-3.00%	21.44%
2008	1087.0	189.5	-10.84%	-1.94%	-3.39%	6.64%	-16.67%	-1.09%	-5.00%	14.20%
2009	1612.0	309.4	-8.51%	-1.19%	-2.08%	6.61%	-16.66%	-0.20%	-3.68%	17.30%

Table 2.2: **Summary Statistics at the firm-year level**

All variables are at the firm-year level and the sample period is from 1991 to 2010. $\frac{I_t}{K_{t-12}}$ is the ratio of current . capital expenditure to beginning of the year net property, plant and equipment. Tobin's Q, Q_{t-12}, is last year's market value of assets divided by the book value of assets, A_{t-1}. A firm's market value of assets equals the book value of assets plus the market value of common stock less the sum of book value of common stock and balance sheet deferred taxes. Cash flow, $\frac{CF_t-12}{K_{t-24}}$, equals the sum of last year's earnings before extraordinary items and depreciation over beginning-of-last-year capital. A firm's price pressure PP_{t-12} is a ratio, in which the numerator is the sum of fund-aggregated holdings purchases of funds for which flows are above the 90^{th} percentile minus the fund-aggregated holdings sales of funds for which flows are below the 10^{th} percentile between 24 and 12 months ago, and the denominator is the average of number of shares outstanding over the same period. $\frac{E_t}{K_{t-12}}$ is cash from sale of common and preferred stocks over beginning of the year net property, plant and equipment. $Churnrate_{t-12}$ is the mutual fund's churn rate projected at the stock-year level and captures the firm's shareholder horizon through the fund's portfolio turnover between 24 and 12 months ago. As in Gaspar et al. (2005), the Mutual Fund Churn rate for fund f in quarter t is as follows: $CR_{f,t} = 2\frac{\sum_{s\in S}|(N_{f,s,t}-N_{f,s,t-3})P_{s,t}|}{\sum_{s\in S}N_{f,s,t}P_{s,t}+N_{f,s,t-3}P_{s,t-3}}$. The Churn rate for firm s in year t is the fund-weighted average of $CR_{f,t}$ of the previous 4 quarters. $\frac{R\&D_t-1}{A_{t-1}}$ is last year's firm-year research and development intensity, which is last year's research and development expenses over beginning of last year's book value of assets. The Kaplan and Zingales (1997) KZ_t financial constraint index is as follows: $KZ_t = -1.001909\frac{CF_t}{K_{t-1}} + 0.2826389Q_t + 3.139193\frac{debt_t}{debt_t+equity_t} - 39.3678\frac{div_t}{K_{t-1}} - 1.314759\frac{Cash_t}{K_{t-1}}$. The Size-Age index of financial constraint, built by Hadlock and Pierce (2010), is as follows: $SA_t = -0.737ln(Size_t) + 0.043[ln(Size_t)]^2 - 0.040Age_t$. $R_{t-13:t-12}$ is the stock return from month t-13 to month t-12. $R_{t-24:t-13}$ is the cumulative stock return from month t-24 to month t-13. $R_{t-48:t-24}$ is the cumulative stock return from month t-48 to month t-24. $R_{t-72:t-24}$ is the cumulative stock return from month t-72 to month t-24. $PP2_{t-12}$, $PP3_{t-12}$ and $PP4_{t-12}$ are alternative definitions of stock price pressure, which can be found in Subsection 2.6.2

Variable	**Obs.**	**Mean**	**Median**	**Std. dev.**
PP_{t-12}	23,487	.002046	.0007147	.003478
$\frac{I_t}{K_{t-12}}$	57,933	.4626	.2206	.7982
Q_{t-12}	36,468	2.147	1.524	1.858
$\frac{CF_t-12}{K_{t-24}}$	53,973	-1.277	.2229	9.714
$\frac{E_t}{K_{t-12}}$	57,610	2.919	.02064	11.85
A_t	65,288	3,747	245.8	33,004
SA_t	61,841	-3.144	-3.087	.7903
KZ_t	38,495	-11.26	-.9413	39.15
ROA_t	59,984	.02621	.1091	.4922
$Churnrate_{t-12}$	24,804	.8265	.7675	.4314
$\frac{R\&D_{t-12}}{A_{t-12}}$	30,728	.1166	.04266	.1962
$R_{t-13:t-12}$	38,372	.02654	.01396	.1535
$R_{t-24:t-13}$	34,969	.1145	.02701	.5594
$R_{t-48:t-24}$	29,444	.2761	.07024	.9077
$R_{t-72:t-24}$	25,105	.681	.2301	1.591
$PP2_{t-12}$	21,773	.01045	.004901	.0161
$PP3_{t-12}$	21,773	.007803	.002454	.01716
$PP4_{t-12}$	22,848	.008558	.005111	.02629

Table 2.3: **Calendar-time portfolio regressions for a portfolio of firms long in high price pressure**

This table reports the coefficient estimates for the intercept term of monthly calendar-time equal-weighted and value-weighted portfolio regressions. The monthly returns are computed for an equal-weighted and a value-weighted portfolio that go long in the top and short in the bottom deciles in stocks sorted by quarterly flow-induced price pressure (PP). The portfolios are rebalanced every quarter and held for up to 12 quarters. Four different monthly returns are reported: the return in excess of the risk-free rate, the CAPM alpha, the Fama-French three-factor alpha and the Fama-French three-factor augmented by the momentum factor. The sample period is from 1993 to 2010. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Equally-weighted

Portfolio holding period	*Excess Return*	*MKT*	*MKT, HML SMB*	*MKT, HML SMB, UMD*
Q0	-0.199%	-0.285%*	-0.097%*	-0.319%**
	(0.002)	(0.002)	(0.002)	(0.001)
Q1-4	-0.669%***	-0.756%***	-0.556%***	-0.618%***
	(0.001)	(0.001)	(0.001)	(0.001)
Q5-8	-0.747%***	-0.839%***	-0.644%***	-0.586%***
	(0.001)	(0.001)	(0.001)	(0.001)
Q5-12	-0.738%***	-0.803%***	-0.623%***	-0.572%***
	(0.000)	(0.000)	(0.000)	(0.000)

Value-weighted

Portfolio holding period	*Excess Return*	*MKT*	*MKT, HML SMB*	*MKT, HML SMB, UMD*
Q0	0.583%**	0.431%*	0.620%***	0.318%
	(0.002)	(0.002)	(0.002)	(0.002)
Q1-4	-0.525%***	-0.707%***	-0.481%***	-0.552%***
	(0.001)	(0.001)	(0.001)	(0.001)
Q5-8	-0.630%***	-0.847%***	-0.571%***	-0.554%***
	(0.001)	(0.001)	(0.001)	(0.001)
Q5-12	-0.629%***	-0.799%***	-0.597%***	-0.563%***
	(0.001)	(0.001)	(0.001)	(0.001)

Table 2.4: **Firm Investment on Lagged Price Pressure**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firm-years with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$								
PP_{t-12}	8.585***		4.837***	5.285***	5.320***	4.883***	3.643***	3.680***
	(1.323)		(1.269)	(1.266)	(1.269)	(1.268)	(1.310)	(1.318)
Q_{t-12}		0.111***	0.080***	0.068***	0.067***	0.056***	0.031***	0.029***
		(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\frac{CF_{t-12}}{K_{t-24}}$		-0.006***	0.001	0.003	0.003	0.003	0.004	0.003
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
$\frac{E_t}{K_{t-12}}$				0.016***	0.016***	0.016***	0.016***	0.015***
				(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
$R_{t-13:t-12}$					0.035	0.029	0.036	0.000
					(0.028)	(0.028)	(0.029)	(0.031)
$R_{t-24:t-13}$						0.059***	0.075***	0.074***
						(0.009)	(0.010)	(0.010)
$R_{t-48:t-24}$							0.036***	
							(0.005)	
$R_{t-72:t-24}$								0.017***
								(0.003)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,140	35,455	21,887	21,475	21,355	21,211	18,244	15,892
R^2	0.419	0.438	0.452	0.470	0.470	0.473	0.450	0.444

Table 2.5: **Fama and MacBeth (1973) Regressions - Future Stock Returns on Current Firm Investment and Lagged Price Pressure**

Fama and MacBeth (1973) regressions are run. The dependent variable is the future monthly stock return from 6 to 18 months after the end of the investment period. The Fama and MacBeth (1973) regressions below consist in two stages. In the first, for each period, cross-sectional OLS estimates are run. In the second stage, the estimated coefficients means and standard errors, which are shown in the table below, are computed. MoM_t is defined as stock momentum and is the abnormal cumulated stock return from months t-24 to t-13. The specifications with *other interactions with* PP_{t-12} include $PP_{t-12} * ln(Q_t)$, $PP_{t-12} * \frac{CF_t}{K_{t-12}}$ and $PP_{t-12} * MoM_t$. The sample contains observations from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $R_{t+6,t+18}$							
$ln(\frac{I_t}{K_{t-12}})$	-0.004***	-0.002*	-0.001	-0.003***	-0.002***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PP_{t-12}		-0.241	-0.502**	-0.252*	-1.040***	-0.272**	-1.074***
		(0.153)	(0.227)	(0.142)	(0.270)	(0.136)	(0.270)
$ln(Q_t)$				0.008***	0.007***	0.008***	0.007***
				(0.002)	(0.002)	(0.002)	(0.002)
$\frac{CF_t}{K_{t-12}}$				0.001***	0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)	(0.000)
$PP_{t-12} * ln(\frac{I_t}{K_{t-12}})$			-0.234*		-0.410***		-0.428***
			(0.126)		(0.133)		(0.137)
MoM_t						0.003	0.003*
						(0.002)	(0.002)
Constant	-0.011**	0.000	0.001	-0.005	-0.004	-0.005	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Other interactions with PP_{t-12}	No	No	Yes	No	Yes	No	Yes
Observations	411,828	261,944	261,944	247,228	247,228	245,528	245,528
R^2	0.026	0.011	0.013	0.029	0.034	0.035	0.041
Number of months	228	225	225	225	225	225	225

Table 2.6: **Future Return on Assets on Current Firm Investment and Lagged Price Pressure**

The dependent variable is the change in return on assets from year t to t+1. Return on assets is operational income before depreciation as a proportion of beginning of year's assets. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: firm fixed effects

Dependent Variable: $\Delta ROA_{t,t+12}$							
$ln(\frac{I_t}{K_{t-12}})$	-0.015***	-0.018***	-0.017***	-0.019***	-0.018***	-0.016***	-0.016***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PP_{t-12}		-0.611***	-1.008**	-0.594**	-1.438**	-0.425*	-1.045
		(0.223)	(0.425)	(0.231)	(0.653)	(0.231)	(0.639)
$ln(Q_t)$				0.004	0.003	0.010***	0.009**
				(0.003)	(0.004)	(0.004)	(0.004)
$\frac{CF_t}{K_{t-12}}$				-0.004***	-0.004***	-0.004***	-0.004***
				(0.001)	(0.001)	(0.001)	(0.001)
$PP_{t-12} * ln(\frac{I_t}{K_{t-12}})$			-0.297		-0.420		-0.273
			(0.243)		(0.303)		(0.292)
MoM_t						-0.021***	-0.019***
						(0.003)	(0.003)
Constant	-0.020***	-0.019***	-0.018***	-0.023***	-0.021***	-0.023***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	31,919	20,194	20,194	18,982	18,982	18,863	18,863
R^2	0.248	0.209	0.209	0.226	0.227	0.240	0.241

Table 2.6: **Future Return on Assets on Current Firm Investment and Lagged Price Pressure (cont.)**

Panel B: industry fixed effects

Dependent Variable: $\Delta ROA_{t,t+12}$							
$ln(\frac{I_t}{K_{t-12}})$	-0.010***	-0.010***	-0.009***	-0.012***	-0.011***	-0.010***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
PP_{t-12}		-0.609***	-1.046***	-0.546***	-1.115***	-0.392***	-0.798**
		(0.148)	(0.196)	(0.132)	(0.363)	(0.133)	(0.399)
$ln(Q_t)$				0.008*	0.008*	0.011***	0.010**
				(0.004)	(0.004)	(0.004)	(0.004)
$\frac{CF_t}{K_{t-12}}$				-0.002***	-0.002***	-0.002***	-0.002***
				(0.000)	(0.000)	(0.000)	(0.000)
$PP_{t-12} * ln(\frac{I_t}{K_{t-12}})$			-0.332**		-0.380**		-0.255
			(0.133)		(0.158)		(0.164)
MoM_t						-0.020***	-0.017***
						(0.003)	(0.003)
$Constant$	-0.020***	-0.015***	-0.013***	-0.019***	-0.018***	-0.018***	-0.017***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Industry Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	31,919	20,138	20,138	18,982	18,982	18,863	18,863
R^2	0.043	0.035	0.035	0.051	0.051	0.059	0.059

Table 2.7: **Firm Investment on Lagged Price Pressure sorted on Financial Constraints - KZ index**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The sample is split into less financially constrained and more financially constrained firms, according to the KZ index of financial constraints. High KZ is the subsample containing firm-years above the KZ median-year, which corresponds to relatively financially constrained firms. Low KZ is the subsample containing firm-years below the KZ median-year, which corresponds to relatively financially unconstrained firms. The Kaplan and Zingales (1997) KZ index in the current year t is as follows: $KZ_t = -1.001909\frac{CF_t}{K_{t-1}} + 0.2826389Q_t + 3.139193\frac{debt_t}{debt_t+equity_t} - 39.3678\frac{div_t}{K_{t-1}} - 1.314759\frac{Cash_t}{K_{t-1}}$. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firm-years with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$										
	High KZ	Low KZ	High KZ	Low KZ	High KZ	Low KZ	High KZ	Low KZ	High KZ	Low KZ
PP_{t-12}	3.001***	6.490**	3.001***	6.455**	2.513***	6.148**	1.663*	5.038*	1.652*	5.451**
	(0.890)	(2.544)	(0.890)	(2.544)	(0.885)	(2.528)	(0.874)	(2.606)	(0.904)	(2.621)
Q_{t-12}	0.073***	0.061***	0.074***	0.060***	0.064***	0.050***	0.041***	0.028***	0.043***	0.020**
	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
$\frac{CF_{t-12}}{K_{t-24}}$	-0.001	0.003	-0.001	0.002	-0.002	0.002	0.001	0.004	-0.001	0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)	(0.006)
$\frac{E_t}{K_{t-12}}$	0.056***	0.013***	0.056***	0.013***	0.057***	0.013***	0.063***	0.013***	0.063***	0.012***
	(0.015)	(0.003)	(0.015)	(0.003)	(0.016)	(0.003)	(0.013)	(0.004)	(0.014)	(0.004)
$R_{t-13:t-12}$			-0.004	0.056	-0.005	0.049	0.017	0.025	0.021	-0.048
			(0.019)	(0.054)	(0.018)	(0.054)	(0.019)	(0.056)	(0.020)	(0.059)
$R_{t-24:t-13}$					0.031***	0.057***	0.045***	0.076***	0.040***	0.088***
					(0.006)	(0.015)	(0.007)	(0.017)	(0.007)	(0.017)
$R_{t-48:t-24}$							0.028***	0.028***		
							(0.004)	(0.010)		
$R_{t-72:t-24}$									0.013***	0.018***
									(0.002)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,714	10,143	10,714	10,143	10,646	10,071	9,190	8,631	7,952	7,566
R^2	0.606	0.511	0.606	0.511	0.610	0.512	0.621	0.495	0.610	0.496

Table 2.8: **Firm Investment on Lagged Price Pressure sorted on Financial Constraints - SA index**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The sample is split into less financially constrained and more financially constrained firms, according to the SA index of financial constraints. High SA is the subsample containing firm-years above the SA median-year, which corresponds to relatively financially constrained firms. Low SA is the subsample containing firm-years below the SA median-year, which corresponds to relatively financially unconstrained firms. The SA Size-Age index of financial constraints, built by Hadlock and Pierce (2010), is as follows: $SA_t = -0.737ln(Size_t) + 0.043[ln(Size_t)]^2 - 0.040Age_t$. Size is equal total assets and is capped above at ln(US$ 4.5 Billion). Age is capped above at 37. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firm-years with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$	High SA	Low SA	High SA	Low SA	High SA	Low SA	High SA	Low SA	High SA	Low SA
PP_{t-12}	3.004	4.752***	3.217	4.756***	3.235	4.222***	3.819	2.900**	4.174	2.834***
	(2.726)	(1.376)	(2.739)	(1.377)	(2.766)	(1.360)	(4.191)	(1.171)	(5.252)	(1.094)
Q_{t-12}	0.058***	0.073***	0.056***	0.073***	0.045***	0.062***	0.023**	0.037***	0.024*	0.036***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.013)	(0.007)
$\frac{CF_{t-12}}{K_{t-24}}$	-0.003	0.019***	-0.004	0.019***	-0.004	0.019***	-0.005	0.017**	-0.007	0.015*
	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.005)	(0.007)	(0.006)	(0.008)
$\frac{E_t}{K_{t-12}}$	0.015***	0.017***	0.015***	0.017***	0.015***	0.017***	0.017***	0.014**	0.017***	0.011*
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
$R_{t-13:t-12}$			0.050	0.011	0.047	0.001	0.070	0.002	0.004	-0.009
			(0.052)	(0.032)	(0.052)	(0.032)	(0.064)	(0.030)	(0.086)	(0.029)
$R_{t-24:t-13}$					0.062***	0.057***	0.072***	0.072***	0.073**	0.066***
					(0.018)	(0.010)	(0.024)	(0.011)	(0.029)	(0.010)
$R_{t-48:t-24}$							0.040***	0.030***		
							(0.013)	(0.006)		
$R_{t-72:t-24}$									0.022**	0.012***
									(0.011)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	6,773	14,702	6,703	14,652	6,598	14,613	4,557	13,687	3,213	12,679
R^2	0.520	0.490	0.518	0.490	0.519	0.494	0.497	0.476	0.513	0.448

Table 2.9: **Firm Investment on Lagged Price Pressure when firms do not go through SEOs in the current and last years**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The sample is now restricted for firms that do not engage in seasoned equity offerings in the current and last years. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firm-years with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$								
PP_{t-12}	5.876***		3.405***	3.508***	3.577***	3.323***	3.039**	3.232**
	(1.252)		(1.241)	(1.252)	(1.254)	(1.252)	(1.359)	(1.434)
Q_{t-12}		0.100***	0.064***	0.057***	0.055***	0.048***	0.029***	0.027***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
$\frac{CF_{t-12}}{K_{t-24}}$		-0.005***	0.005	0.006	0.007*	0.007*	0.008*	0.008
		(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
$\frac{E_t}{K_{t-12}}$				0.023***	0.023***	0.023***	0.023***	0.024***
				(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
$R_{t-13:t-12}$					0.042	0.039	0.047*	0.025
					(0.029)	(0.029)	(0.029)	(0.030)
$R_{t-24:t-13}$						0.039***	0.058***	0.054***
						(0.010)	(0.012)	(0.011)
$R_{t-48:t-24}$							0.038***	
							(0.006)	
$R_{t-72:t-24}$								0.016***
								(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,713	31,039	18,646	18,277	18,161	18,068	15,995	14,111
R^2	0.453	0.428	0.470	0.490	0.491	0.493	0.475	0.464

Table 2.10: **Firm Investment on Lagged Price Pressure sorted on Shareholder Horizon - Mutual Fund Churn Rate**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The sample is split into short horizon shareholder firms and long horizon shareholder firms, according to the mutual fund churn rate measure. As in Gaspar et al. (2005), the mutual fund churn rate for fund f in quarter t is as follows: $CR_{f,t} = 2\frac{\sum_{s\in S}|(N_{f,s,t}-N_{f,s,t-3})P_{s,t}|}{\sum_{s\in S}N_{f,s,t}P_{s,t}+N_{f,s,t-3}P_{s,t-3}}$. The Churn rate for firm s in year t $CR_{s,t}$ is the fund-weighted average of $CR_{f,t}$ of the previous 4 quarters. Short horizon shareholder firms are those with high churn rate, in the top 3 deciles of the yearly distribution of $CR_{s,t-12}$. Long horizon shareholder firms are those with low churn rate, in the bottom 3 deciles of the yearly distribution of $CR_{s,t-12}$. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$	High CR	Low CR	High CR	Low CR	High CR	Low CR	High CR	Low CR	High CR	Low CR
PP_{t-12}	8.085***	1.195	8.058**	1.410	7.679**	1.140	7.120**	1.769	6.535**	3.565
	(3.130)	(2.201)	(3.163)	(2.203)	(3.165)	(2.188)	(3.569)	(2.209)	(3.252)	(2.274)
Q_{t-12}	0.062***	0.062***	0.063***	0.057***	0.051***	0.046***	0.038***	0.025*	0.023	0.025**
	(0.013)	(0.012)	(0.013)	(0.011)	(0.013)	(0.012)	(0.015)	(0.013)	(0.016)	(0.012)
$\frac{CF_{t-12}}{K_{t-24}}$	0.011	-0.007	0.011	-0.007	0.010	-0.007	0.012	-0.010	0.016	-0.013
	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.007)	(0.010)	(0.008)	(0.012)	(0.011)
$\frac{E_t}{K_{t-12}}$	0.019***	0.014**	0.019***	0.014**	0.020***	0.014**	0.019**	0.015*	0.017**	0.015*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.009)
$R_{t-13:t-12}$			-0.051	0.178**	-0.053	0.156**	-0.039	0.172**	-0.102	0.122
			(0.068)	(0.074)	(0.068)	(0.073)	(0.075)	(0.076)	(0.081)	(0.082)
$R_{t-24:t-13}$					0.061***	0.052**	0.067***	0.086***	0.078***	0.092***
					(0.020)	(0.021)	(0.025)	(0.024)	(0.027)	(0.020)
$R_{t-48:t-24}$							0.019	0.038***		
							(0.017)	(0.011)		
$R_{t-72:t-24}$									0.023*	0.013**
									(0.012)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	6,039	6,344	5,989	6,294	5,942	6,257	4,967	5,407	4,243	4,705
R^2	0.610	0.597	0.609	0.599	0.611	0.603	0.583	0.605	0.581	0.617

Table 2.11: **Firm Investment on Lagged Price Pressure sorted on Research and Development Intensity**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The sample is split into firms with high intensity in research and development and low intensity in research and development. Each year, a firm falls in the high (low) intensity category if its last year's research and development expenses as a ratio of beginning of last year's assets is above (below) the median. $HighR\&D$ and $LowR\&D$ are respectively the subsets of high and low R&D intensity firms sorted according to R&D intensity in the previous year. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The sample contains annual observations and its period ranges from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$	High R&D	Low R&D	High R&D	Low R&D	High R&D	Low R&D	High R&D	Low R&D	High R&D	Low R&D
PP_{t-12}	8.141**	4.633**	8.231**	4.643**	7.848**	4.757**	7.387*	2.404	7.520*	2.267
	(3.244)	(2.202)	(3.249)	(2.215)	(3.263)	(2.229)	(3.817)	(1.624)	(3.885)	(1.750)
Q_{t-12}	0.061***	0.086***	0.059***	0.085***	0.046***	0.076***	0.022**	0.033***	0.015	0.041***
	(0.007)	(0.017)	(0.008)	(0.017)	(0.008)	(0.018)	(0.009)	(0.010)	(0.010)	(0.011)
$\frac{CF_{t-12}}{K_{t-24}}$	-0.003	0.020**	-0.003	0.020**	-0.003	0.020**	-0.002	0.013	-0.002	0.013
	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.008)	(0.005)	(0.009)	(0.006)	(0.023)
$\frac{E_t}{K_{t-12}}$	0.014***	0.012	0.014***	0.012	0.014***	0.011	0.015***	0.011	0.014***	0.013
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.004)	(0.013)	(0.004)	(0.013)
$R_{t-13:t-12}$			0.059	0.007	0.060	0.015	0.068	-0.016	0.023	-0.000
			(0.058)	(0.044)	(0.058)	(0.043)	(0.060)	(0.040)	(0.068)	(0.045)
$R_{t-24:t-13}$					0.080***	0.033***	0.105***	0.051***	0.113***	0.042***
					(0.018)	(0.013)	(0.020)	(0.011)	(0.022)	(0.013)
$R_{t-48:t-24}$							0.052***	0.024***		
							(0.011)	(0.008)		
$R_{t-72:t-24}$									0.032***	0.006
									(0.007)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	6,219	6,679	6,195	6,653	6,141	6,615	5,037	5,879	4,193	5,266
R^2	0.436	0.592	0.435	0.592	0.440	0.592	0.409	0.565	0.421	0.556

Table 2.12: **Robustness Test: Higher order Moments Estimator**

Erickson and Whited (2002) and Erickson and Whited (2000) higher-order moments estimators are run, in which the mismeasured regressor is Q_{t-1}. I use the Stata code provided in Toni Whited's website, which executes the estimators and the identification diagnostic tests for unbalanced panels developed in Erickson and Whited (2012). The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. The higher-order moments estimators are on columns 2,3,4,6,7 and 8. Standard OLS regressors estimates are shown on columns 1 and 5. Parentheses below the estimates show standard errors. The OLS standard errors are adjusted for heteroskedasticity using the White procedure. τ^2 is the R^2 of the measurement equation, which is an index of measurement quality. This index ranges between zero and one, with zero indicating a worthless proxy and one indicating a perfect proxy. The sample contains observations from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$								
	OLS	GMM5	GMM6	GMM7	OLS	GMM5	GMM6	GMM7
PP_{t-12}	6.654***	222.516***	117.079***	52.537***	2.879***	88.678***	61.763***	55.874***
	(0.948)	(0.000)	(0.000)	(0.000)	(0.986)	(0.000)	(0.000)	(0.000)
Q_{t-12}	0.074***	0.062***	0.062***	0.062***	0.038***	0.032***	0.032***	0.032***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
$\frac{CF_{t-12}}{K_{t-24}}$	0.004**	0.003**	0.003**	0.003**	0.004**	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\frac{E_t}{K_{t-12}}$	0.019***	0.021***	0.021***	0.021***	0.021***	0.019***	0.019***	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$R_{t-13:t-12}$					-0.001	0.075**	0.075**	0.075**
					(0.026)	(0.032)	(0.032)	(0.032)
$R_{t-24:t-13}$					0.078***	0.062***	0.062***	0.062***
					(0.008)	(0.011)	(0.011)	(0.011)
$R_{t-72:t-24}$					0.024***	0.015***	0.015***	0.015***
					(0.002)	(0.003)	(0.003)	(0.003)
Firm Fixed Effects	No	No	No	No	No	No	No	No
Observations	21,475	21,475	21,475	21,475	15,892	15,892	15,892	15,892
R^2	0.161	0.229	0.225	0.225	0.149	0.779	0.774	0.775
τ^2		0.012	0.036	0.036		0.032	0.063	0.068

Table 2.13: **Robustness Test: Firm Investment on Lagged Price Pressure across Different Price Pressure Variables**

The dependent variable is the ratio of current annual capital expenditure to beginning of year net property, plant and equipment. Firm fixed effects and year effects are used in all OLS regressions. The reported standard errors in parentheses are adjusted for clustering of the residual at the firm level. The coefficients shown below are for the lagged price pressure only. See Subsection 2.6.2 for the definition of the price pressure variables. Each row represents a different price pressure variable as main regressor. In all specifications, lagged Tobin's Q, cash from equity issuance over lagged capital and lagged cash flow as a proportion of beginning of year capital are included. Moreover, each column has a different set of additional past stock returns as controls, as specified in the column headline. The sample contains annual observations and its period ranges from 1992 to 2010. Only firms with more than 1% aggregate mutual fund ownership are included. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: $\frac{I_t}{K_{t-12}}$				
Price Pressure Variable	No Returns Controls	$R_{t-13:t-12}$	$R_{t-13:t-12}$ $R_{t-24:t-13}$	$R_{t-13:t-12}$ $R_{t-24:t-13}$ $R_{t-72:t-24}$
PP_{t-12}	5.285***	5.320***	4.883***	3.680***
	(1.266)	(1.269)	(1.268)	(1.318)
$PP2_{t-12}$	0.849***	0.852***	0.632***	0.483**
	(0.223)	(0.223)	(0.222)	(0.224)
$PP3_{t-12}$	0.814***	0.812***	0.658***	0.532**
	(0.217)	(0.218)	(0.216)	(0.221)
$PP4_{t-12}$	0.336**	0.337**	0.264	0.094
	(0.167)	(0.166)	(0.166)	(0.139)
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
SE Clustered at the Firm Level	Yes	Yes	Yes	Yes

Table 2.14: **Number of Firms that Issued at least 1 SEO in the Current Year**

This table reports the number of firms that issued at least 1 seasoned equity offering by year. The data comes from Thomson Securities Data Center. The annual sample varies from 1991 to 2010.

Year	**Number of Firms**
1991	439
1992	479
1993	722
1994	474
1995	590
1996	696
1997	619
1998	457
1999	407
2000	365
2001	353
2002	347
2003	402
2004	455
2005	374
2006	393
2007	406
2008	280
2009	706
2010	667
TOTAL	9,631

Chapter 3

Information Asymmetries in Global Institutional Investment

Co-authored with Harald Hau (University of Geneva) and Hélène Rey (London Business School)

3.1 Introduction

Institutional investors enjoy a privileged access to executive officers and meet them frequently. According to survey data, chief executives and chief financial officers dedicate 17 and 26 days per year to briefing their most important shareholders, respectively. Do corporate executive pass on private information on such occasions which allow institutional investors to time the market? Do the rare cases of insider trading brought against fund managers hide an economically significant information asymmetry in favor of institutional investors?

This paper examines more than 8 million institutional trades over the period 1999 to 2009 for their information content and finds strong evidence for institutional market timing ability for large sell transactions in corporations where they hold large stakes.

The main results of this paper are threefold. First, we show that funds have skills to sell their holdings but they experience losses in semesters that follow large holding increases. By running quantile regressions of the change in portfolio weights over the last six months on the risk-controlled stock return over the next 6 months, we are able to discern a S-shape, shown in Figure 3.2, consistent with the fact that funds are able to sell their positions before negative stock returns, but do not increase their holdings ahead of future positive stock returns. If the average OLS coefficient is negative and significant at -0.625, indicating there is no stock picking skill on average, the significant coefficients at the 5% and 95% quantiles, respectively 1.549 and -5.029, are consistent with skill only when funds are reducing or selling their stock holdings. Second, when we introduce the dummies for international/domestic funds and home/foreign stock positions, we can discern an advantage for local funds. At the quantile 5%, the coefficient of the dummy for International Fund investing at Home is -0.447 and the coefficient of the dummy for International Fund investing abroad is -0.851. If we compare them to the baseline coefficient of 1.549, this corresponds to a 29% and 55% lower market timing ability for the international/home and international/foreign funds, respectively. Those are consistent with distance negatively affecting market timing ability for selling stocks. Finally, we show that the superior skill in selling stocks might be consistent with insider information. We sort our observations into *small positions* and *large positions* subsamples, in which the fund portfolio weights and the share of the fund in the total stock market capitalization are taken into account. We argue that insider information is more important in the *large positions* subsample and we run quantile regressions of the change in past weights on future excess stock return for both subsets. As seen in Figure 3.5, the coefficient for the 5% quantile for the *large positions* subsample is 4.641, which is considerably higher than the 1.549 coefficient in the full sample regression. In the *small positions* subsample, we don't find market timing ability in the 5% quantile.

Academic research on information asymmetries has mostly focused on portfolio performance rather than individual trades. But portfolio performance is likely to reflect many separate investment decisions as well as the investment mandate and risk constraints of the entire fund. By unbundling the portfolio and moving to the trade level, we can condition the analysis on individual trade and stock characteristics; thus gaining in statistical precision. In particular, we can focus on the part of the trade distribution of institutional investors which should be most informative about any private information: large sell trades in stocks in which the investor was previously holding a large stake. Institutional investors are most likely to obtain private information in stocks in which they are important shareholders both in terms of their own portfolio weight or in terms of the percentage of their ownership relative to the market capitalization. Since positive information is not actionable for equity funds which hold already a very large position and cannot trade in derivatives, it is primarily negative private information which should trigger a large position change and a strong negative correlation between institutional sell trades and consecutive negative excess returns for the stock under consideration.

An alternative explanation for our results is that fund managers make systematically better market timing decisions for sell trades based on public information only. But this interpretation of the data begs the question why the same managers are unable to make informed buy trades in stocks in which they are not yet large shareholders and thus benefit from a close interaction with corporate managers. While we cannot exclude that the information processing skills of institutional investors are fundamentally different for negative and positive corporate news, we believe that such an interpretation has only very limited plausibility.

The clearest evidence that meetings between corporate officers and fund managers provide trading advantages for the latter comes from a recent case study by Solomon and Soltes (2012). For a single mid-size stock traded in the NYSE, they analyze the entire meeting record of senior management with institutional investors from November 2004 to March 2010. The likelihood of a meeting between senior managers and a fund manager increases with the fund's investment position in the firm and decreases in geographical distance. Importantly, meetings with senior corporate officers improve the market timing ability of the fund manager in this particular stock. While lacking microdata on the local interaction between corporate officers and institutional investors, we investigate the same market timing ability for a representative stock sample covering a large proportion of the global institutional investor universe.

Security regulation on Fair Disclosure (i.e. Reg FD) passed in 2000 has as an objective to prevent certain investors from gaining an unfair advantage in the financial market through preferential access to information. While such regulation did not prohibit one-on-one meetings between investors and corporate officers, it specifies that all material information disclosed by the manager had to be publicly available and accessible to all investors. Yet, since 2000, the SEC has brought only five cases against firms for violating Fair Disclosure in regards to private meetings with investors (Solomon and Soltes (2012)). Prosecuting fund managers for insider trading is also very difficult notwithstanding a few rare and prominent recent cases. [1]

Our study is linked to the literature that investigates whether mutual funds outperform the market in a persistent way, which is far from having a unique view. Daniel, Grinblatt, Titman and Wermers (1997) suggest that mutual funds, in special aggressive-growth funds, possess some stock picking skills but not timing skills using characteristic-based benchmarks, which are constructed using 125 passive portfolios and then are matched to the funds portfolio based on the size, value and momentum characteristics. Brown and Goetzmann (1995) find performance persistence in equity mutual funds in a dataset free from survivorship bias and attribute it to funds that lag passively the S&P500. Other papers, in contrast, argue that mutual fund managers do not possess superior stock picking skills. Malkiel (1995) looks into equity mutual

[1] An example is the high profile court case against the fund manager Raj Rajaratnam in May 2011, who was found guilty of trading on corporate inside information. The jury verdict mostly relied on self-incriminating telephone conversations rather than the trading pattern, which the defendant justified as the result of public information and investment research.

fund returns from 1971 to 1991 in a dataset free of survivorship bias and conclude that mutual funds underperform the market even before accounting for reported expenses with the exception of load fees. They also fail to detect persistence in mutual fund performance for the 1980s, though they do for the 1970s. Gruber (1996) argues that investing in the mutual fund industry is rational, as investors can make money even when the average mutual fund underperforms: it is worth to invest in active mutual funds as future performance is partially predictable from past performance. Carhart (1997) dismisses the *hot hands* hypothesis, in which individual fund managers have superior skills, in order to explain persistence in mutual fund performance. Using a sample free of survivorship bias, he finds that persistence is down to expenses, transaction costs and common factors in stock returns. He also shows that funds that follow momentum strategies do not earn superior returns. Our paper contributes by investigating whether fund managers trades as reactions to future stock returns are heterogeneous.

Our results strongly reject the homogeneity of portfolio weight changes as a function of future stock returns and find suggestive evidence linking it to insider information fund managers might have access in boards of firms in which they hold an important stake. In that respect, our paper relates to the literature that studies private information of corporate executives. Peyer and Vermaelen (2009) argue that positive abnormal returns following share repurchase programs can be explained by the overreaction hypothesis, which states that stocks that suffered a severe price decline in the 6 months leading to the repurchase are undervalued. The share repurchase program is how firm managers' send a signal to the market that the current public information on the firm is worse than it should be.

We also show that funds that are more distant from the firms they invest in have less access to private information. Other papers have similar findings. Hau (2001) shows how distance affects stock trading profits. By using a detailed dataset that contains the location of traders that trade in the electronic trading system Xetra, in Germany, he finds that traders located outside Germany underperform the ones located in Germany, in special for the largest German blue-chip stocks. He further finds evidence of informational advantage of proximity to corporate headquarters of the traded stock for intraday trading. Coval and Moskowitz (2001) provide evidence that mutual fund managers have superior information on local stocks. The average fund manager earns a superior return for her local holdings relative to the nonlocal ones. Also, local stocks held by the fund manager outperform local stocks not held by her. Those effects are stronger if funds are smaller, have few holdings and are older. Also, they are more pronounced in small cities and small locations, locations in which outsiders would have a harder time obtaining information. They further show that local ownership of stocks positively and significantly predict abnormal returns.

Our paper continues as follows. In Section 3.2, we lay out the hypothesis on heterogeneous market timing ability and propose how to test it. In Section 3.3, we describe the data and the screening procedures we take. In Section 3.4, we discuss results and argue how insider information might be linked to the heterogeneous responses in mutual fund trades. Finally, in Section 3.5, we conclude.

3.2 Hypotheses

Survey evidence documents that managers of publicly traded firms spend considerable time meeting investors – on average 17 and 26 days per year for chief executive officers and chief financial officers, respectively. Such "informal contacts" can take the form of public conference meetings sponsored by investment banks, or more private meetings at corporate headquarters or direct at the investor's office.

As documented by Solomon and Soltes (2012), large institutional investors are more likely to have privileged access to top management. For a single U.S. company, they document that such meetings increase the market timing ability of the investors. Our first hypothesis is that such market timing ability is a general feature of institutional trading:

Hypothesis 1: Information Advantage of Institutional Holders

Institutional investors have privileged information access to management which improves their market timing ability. If they already hold a large stake, their information advantage should primarily come from negative information triggering block liquidations. Stock acquisitions are not informative trades if they generally precede access to inside information.

Institutional investors are likely to have limits with respect to the positions they can take in any single stock. Having a large block enables them to obtain inside information, but they may not be able to increase this position further on positive news nor are they allowed to benefit from derivative trading in such a situation. However, negative information about the firms prospects can be exploited as the fund can liquidate or at least reduce its stake. Information advantages of institutional investment therefore give rise to an asymmetric market time ability with respect to position liquidations but not position acquisitions. The empirical part uses quantile regressions to infer the correlation of the holding change with future excess returns for different quantiles of the portfolio weight change. According to hypothesis 1, the most negative portfolio weight changes should yield the highest correlation with future excess returns.

Building a privileged relationship with top managers may nevertheless be a time consuming activity, and more feasible for funds with relatively few stock investments. A lower degree of portfolio diversification may also allow the manager to specialize in companies which provide better private information flows to their block holders.

Both arguments suggest that the asymmetric market timing ability of funds is more pronounced for the less diversified funds:

> **Hypothesis 2: Information Advantage and Investor Diversification**
>
> *Less diversified investors have a larger incentive to solicit private information from firm management and/or should pick stocks for which private information is most abandoned. Liquidation of their stock holdings should be particularly informative.*

Firm management might also be more willing to pass inside information to institutional investors which hold large stakes in the firm. The size of the investment share relative to the stocks market capitalization therefore provides an additional dimension on which we can sort institutional investors:

> **Hypothesis 3: Information Advantage and Investment Size**
>
> *Investors with large (or controlling) equity stakes in the corporation have better access to management's inside information. A fund's timing ability with respect to position liquidations should increase for funds with larger stakes relative to the stock's market capitalization.*

In order to obtain evidence for both hypothesis 2 and 3, we can sort all fund positions according to (i) their size relative to the fund capitalization and (ii) their size relative to the stock capitalization. The empirical part will undertake a sorting in terciles in both dimensions and report quantiles regressions for each of the 9 buckets. We expect the bucket with the most concentrated fund positions and the largest equity stakes relative to stock capitalization to feature the highest sell/buy asymmetry with respect to market timing ability.

Geographical distance makes it more difficult for fund managers to interact with senior corporate managers. In their case study, Solomon and Soltes (2012) confirm that the distance between the fund location and the corporate headquarter indeed significantly reduces the probability of a meeting between senior managers of a single firm and fund managers even within the U.S. The international scope of our holding data provides an opportunity to test for international information asymmetries in fund management:

Hypothesis 4: Information Advantage and Investor Location

Geographically distant investors find it relatively harder to obtain inside information from management. Their negative holding changes should be relatively less informative about future excess returns.

A geographical information advantage might also have its cause in aspects other than the costs of physical encounter which increases in distance. Social networks typically also have a geographical dimension and might re-enforce the information disadvantage of fund managers in other countries. Similarly, language or culture might also present additional barriers to tapping into the private information of senior corporate managers. Unfortunately, our data lacks the detailed information on fund managers and firm management to distinguish these aspects.

3.3 Data

Our data on mutual fund equity holdings come from the Thomson Reuters database, which contains information on equity mutual funds worldwide. The sample contains half-yearly observations from 1999 to 2009. The holdings file records fund name, management company name, country code, and reporting date. In addition, it provides the security number, security country code, shares outstanding, and number of shares held by a fund. Reporting for most international funds occurs only at six-month intervals, which obliges us to undertake the analysis at a semi-annual frequency. We note that the Thomson Reuters data account for both pure equity funds and the equity holdings of balanced funds, which also hold other assets such as bonds. However, such additional asset positions (other than equity) are not part of the data and cannot be otherwise inferred. We also note that fund attribution of equity holdings might slightly deviate from the reporting on international fund positions by the Investment Company Institute (ICI), as can be seen in Figure 3.1. For example, some management companies create subsidiary funds in other countries to distribute their fund management services. The Thomson database treats such "feeder funds" as separate entities and attributes them to their respective country of registration even if the actual investment management occurs elsewhere.[2] We always retain the last reporting date within the last 3 months of each semester[3], even if the fund features multiple reporting dates within a semester. The reported fund holdings are matched with the end-of-semester stock price data from Datastream. All return calculations are based on the total return index to account for dividend payments and capital measures.

We implement a series of filters in order to guarantee data reliability. First, we eliminate all fund-semesters for which total net assets is less than US$ 10 Million, as we think very small funds could bias our data. Second, we eliminate all highly concentrated fund-semesters for which the Herfindahl index is above 20%[4]. Funds

[2] This aspect may explain the small discrepancies with respect to the number of funds per country between our data and the fund statistics from the Investment Company Institute (ICI).

[3] If the last reporting date is within the first 3 months of a semester, we ignore the observation.

[4] We define the fund-semester Herfindahl index as $H_{f,t} = \sum_{s=1}^{N} \omega_{f,s,t}^2$, in which $\omega_{f,s,t}$ is stock s's weight in fund f's portfolio in semester t. A very concentrated fund-semester has a high Herfindahl index.

with highly concentrated portfolios might have incentives which could bias our results. Third, we delete observations that are probably data errors, such as negative holdings, a single fund-semester-holding with value higher than US$ 30 Billion or observations for which the cumulated 6-month stock return is lower than -80% or higher than 500%.

Table 3.1 summarizes fund holdings for December 2007 by mutual fund domicile. A total of 19,296 funds reported stock positions with a combined total net equity value of US$ 8.7 Trillion. Around 65% of the value of the reported equity holdings in our sample concern U.S. domiciled funds. We classify as international funds all fund-semesters than invest at least 10% of the value of the portfolio in foreign stocks. The international funds represent 65% of all funds and hold around 62% of all assets in our dataset in December 2007. Those numbers are slightly lower (42% and 54%, respectively) for US funds, suggesting they are home-biased.

The fund coverage in the Thomson Reuters database is comparable to the Lionshares database used by Cremers, Ferreira, Matos and Starks (2011), who reported total net equity assets of US$ 8.0 Trillion for December 2007. We can also compare our reported aggregate country holdings to the ICI international fund statistics.[5] The correlation between our reported holdings and those reported by ICI (in logs of US$ Million of equity fund assets) is 96.0% across countries.

Finally, we adjust stock returns for international and local risk factors. We regress each 6-month cumulated raw stock return on 8 factors: local market, local value, local size, local momentum, non-local market, non-local value, non-local size and non-local momentum. We then use the residual of this regression as our 6-month cumulated risk-controlled stock return. The non-local factors are factors averaged across all countries except the local one.

[5]See the 2011 Investment Company Factbook, 51st edition, pages 187-188, available at www.icifactbook.org.

The summary statistics on stock returns along with other control variables can be found on Table 3.2. The dependent variable dw, the change in weights from month t-6 to month t, is multiplied by 1000 and can vary between -1000 and 1000. The control variables are defined as follows. Home IF is the interaction of the dummy Home with the dummy International Fund. The dummy Home assumes value 1 only and if only fund and stock are located in the same country. The dummy International Fund assumes value 1 only and if only a fund invests more than 10% of its TNA in foreign stocks in a certain period. Foreign IF is the interaction of the dummy Foreign with the dummy International Fund. The dummy Foreign assumes value 1 only and if only fund and stock are not located in the same country. US IF, UK IF, Eurozone IF and Other IF are the US, UK, Eurozone and Other countries dummies interacted with the International Fund dummy, respectively. These country dummies assume value 1 only and if only the fund is located in the country to which the dummy refers to. US refers to the United States. UK refers to the United Kingdom. Eurozone refers to Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia or Spain. Other countries refer to all countries that are not the United States, the United Kingdom or one of the Eurozone countries. Fund Size is the Total net assets in dollars held by the fund in a certain period. Stock size is the total market capitalization in dollars of a stock in a certain period. Fund positions is the number of stock positions held by a fund in a certain period. All the listed control variables are also interacted with the risk adjusted excess returns to form new control variables.

3.4 Evidence on Information Asymmetries

Quantile regressions (QR) are ideally suited when there is likely to be a large heterogeneity in responses to changes to a variable of interest[6]. This is precisely the case in our application where there are many reasons to believe that differential access to information, for example, may be an important unobserved determinant of portfolio weight changes of mutual funds in reaction to changes in future expected returns. Quantile regressions (see Koenker (2005)) yield different estimated slopes which vary across the conditional distribution of the variable we seek to explain. An additional advantage of using QR is that thes estimates are robust to non Gaussian distributions of the error terms.

In our framework we are attempting to explain portfolio weight changes as a function of future expected stock returns $R_{j,t+1}$. We define portfolio weight changes as:

$$\begin{aligned} dw_{i,j,t} =& \alpha + R_{j,t+1} + Home_{i,j,t} * IF_{i,t} + Foreign_{i,j,t} * IF_{i,t} + FundSize_{i,t} + StockSize_{j,t} + \\ & + NumberFundPositions_{i,t} + Home_{i,j,t} * IF_{i,t} * R_{j,t+1} + Foreign_{i,j,t} * IF_{i,t} * R_{j,t+1} + \\ & + FundSize_{i,t} * R_{j,t+1} + StockSize_{j,t} * R_{j,t+1} + FundPositions_{i,t} * R_{j,t+1} + \\ & + \epsilon_t \end{aligned}$$

in which $dw_{i,j,t} = w_{i,j,t} - w_{i,j,t-1}$ is the change in the weight of stock j in fund i's portfolio from semester t-1 to semester t; $R_{j,t+1}$ is the stock j's future risk-controlled return[7] from semester t to semester t+1; $Home_{i,j,t}$ is a dummy that takes value 1 only and if only fund i and stock j are located in the same country in semester t; $Foreign_{i,j,t}$ is a dummy that takes value 1 only and if only fund i and stock j are not located in the same country in semester t; $IF_{i,t}$ is an international fund dummy that

[6]For a very interesting use of QR in macroeconomics see Misra and Surico (2011). We thank Paolo Surico for very helpful insights and follow largely here the discussion of Misra and Surico (2011) on the usefulness of quantile regressions .

[7]We use 8 factors as risk controls: (local and non-local) interacted with (market, value, size and momentum).

takes value 1 only and if only at least 10% (in dollar terms) of the fund i's portfolio is invested in foreign stocks in semester t; $Fund\ Size_{i,t}$ represents the aggregate value of the fund i's equity portfolio (measured in log of millions of U.S. dollars) in semester t, $Stock\ Size_{j,t}$ denotes the market capitalization of stock j (measured in log of millions of U.S. dollars) in semester t, and $Fund\ Positions_{i,t}$ measures (in logs) the number of the fund i's stock positions in semester t. $Home_{i,j,t} * IF_{i,t}$ is dummy that takes value 1 only and if only an international fund i invests in a stock j located in the same country in semester t. $Foreign_{i,j,t} * IF_{i,t}$ is dummy that takes value 1 only and if only an international fund i invests in a stock j located abroad in semester t. All control variables are included as interacted with the excess return ($\times R_{j,t+1}$).

The quantiles of the potential distributions of weight changes conditional on covariates $R_{j,t+1}, X_{i,j,t}$ are given by

$$Q_{dw_{ijt}/R_{j,t+1},X_{i,j,t}}(\tau)$$

with τ in $(0,1)$ and $X_{i,j,t}$ are control variables (including dummies).

The effect of an expected stock return change on different points of the marginal distribution of the potential weight changes is

$$\frac{\partial Q_{dw_{ijt}/R_{j,t+1},X_{i,j,t}}(\tau)}{\partial R}$$

The quantile regression model we are using is the following:

$$dw_{i,j,t} = q\left(R_{j,t+1}, X_{i,j,t}, \lambda_{i,j,t}\right)$$

where $\lambda_{i,j,t}$ conditional on $R_{j,t+1}, X_{i,j,t}$ follows a uniform distribution on $(0,1)$.

$q\left(R, X, \tau\right)$ is the conditional τ^{th} quantile of dw given $R = R_{j,t+1}$, $X = X_{i,j,t}$. The term $\lambda_{i,j,t}$ parameterizes the unobserved heterogeneity across fund manager-stock trades having the same characteristics $X_{i,j,t}$ and reacting to the same expected future adjusted return change $R_{j,t+1}$. It determines the relative ranking of fund-stock trades in terms of portfolio weight changes.

For each quantile τ we specify the following linear model

$$Q_{dw_{ijt}}(\tau) = \alpha_1(\tau)' X_{i,j,t} + \alpha_2(\tau) R_{j,t+1}$$

where our main interest lies in the estimated parameters $\alpha_2(\tau)$ which we plot by quantiles in Figure 3.2. If fund managers are price takers in the stock markets, the $\alpha_2(\tau)$ measure the causal effect of expected risk adjusted returns changes on portfolio weight changes. holding the unobserved characteristic driving heterogeneity fixed at $\lambda_{i,j,t} = \tau$. Then

$$P(dw \leq q(R, X, \tau)/R, X) = P(\lambda \leq \tau/R, X) = \tau$$

We present the results for both conditional and unconditional quantile regressions in Table 3.3.

3.4.1 Heterogeneity in Market Timing Ability

The first observation is that in our sample there is wide heterogeneity in slopes: looking only at the OLS estimates would miss an enormous amount of information in our sample. In other words homogeneity of reactions of fund managers trades is strongly rejected by the data. Second, for a non negligible part of the sample, expected stock return changes do not lead to any portfolio weight adjustments (or leads to very minor ones). Third, there are some "big winners" (as measure by a strong positive correlation between expected returns and dw) and some "big losers" (strong negative correlation between dw and expected returns).

According to hypotheses in Section 3.2, the size and direction of holding changes are directly related to the information content of the respective trades. We run separate quantile regression at the 5%, 10%, 25%, 50%, 75%, 90%, and 95% quantiles. The baseline regression in Table 3.3, Panel A, includes the excess return in the consecutive semester ($R(t+1)$) as the only regressor (apart from a constant).

The regression coefficient for the excess return in Panel A decreases monotonically from a highly significant positive coefficient of 1.549 for the 5% quantile to -5.029 for the 95% quantile. Figure 3.2 shows the quantile coefficient for future excess return plotted for all quantiles; it shows an S-shaped pattern with highly significant coefficients for the tail quantiles. The last column in Table 3.3, Panel A, reports the OLS coefficient, which captures the mean covariance with the excess return. The OLS coefficient is negative at -0.625 in contrast to the highly positive coefficient for the 5% and 10% quantile.

We will now attempt to identify the characteristics of the funds which perform the most successful stock picking. We rerun the the baseline regression in four different subsamples: (i) only non-positive change in weights $dw_t \leq 0$; (ii) only positive change in weights $dw_t > 0$; (iii) only non-positive future excess stock returns $R_{t+1} \leq 0$; (iv) only positive future excess stock returns $R_{t+1} > 0$); We present results in Figure 3.3, from which we can infer that stock picking skill is only present for non-positive values of dw_t and for non-positive values of ER_{t+1}. Even stronger it is the pattern in (i) and (ii), in which all the positive coefficients, associated with stock picking skills, are on the non-positive range of dw_t and all the negative coefficients are on the positive range of dw_t. While the pattern in (iii) and (iv) is still consistent with stock picking abilities being only present when selling stocks (negative change in weights ahead of future negative excess returns), the higher quantiles in (iii) suggest that some of the future negative excess returns are not correlated with a negative change in weights.

The 4 subsamples quantile regressions are consistent with stock picking skill being present only for negative change in past weights and negative future excess returns, which seems to suggest that funds are skillful only when selling holdings. These positive coefficients for large holding reductions confirm the market timing ability of institutional investors with respect to asset selling (Hypothesis 1). On the other hand, these institutional investors experience investment losses in the semester that follows large holding increases in the 90% and 95% quantiles of portfolio weight changes. The latter effect could result from the price pressure which such large position increases generate for the stock price in period t. Reversal of this stock price in the consecutive period $t + 1$ can generate a negative conditional correlation for the upper quantiles of portfolio changes.

In Panel B, the single coefficient on future excess return is split into various interaction terms. Interaction terms include (i) a constant, (ii) a dummy variable marking international funds with a location matching the country of the stock's incorporation ($Home\ IF$), (iii) a second dummy marking international funds for which fund location and stock location differ by country ($Foreign\ IF$), (iv) a control for $Fund\ size$ (log of fund assets), (v) a measure of $Stock\ size$ (log of stock capitalization) and (vi) fund diversification captured by the number of $Fund\ positions$ (also in logs). The specification in Panel B also includes these six variables separately without the excess return as interaction term (not reported).

At each quantile, other trade characteristics apart from the portfolio weight may influence market timing success. Other conditioning variables in Table 3.3, Panel B, are the fund type, fund size, stock size and fund diversification change in parallel. For example, more diversified funds might find it more difficult to build a privileged relationship with senior managers of all the firms the fund is invested in. Interestingly, the coefficient on the number of $Fund\ positions$ in the 5% and 10% quantiles is significantly lower. A decrease in the number of fund position by two standard deviations (or 1.51) implies an increase in the market time ability at the 5% quantile of 19.3% relative to the baseline coefficient of 1.549 in Panel A. On the other hand, $Fund\ size$ is associated negatively with market timing at the 5% quantile; an increase by two standard deviations of the fund size (or 3.21) comes with a coefficient decrease of -0.244 or -15.7% relative to the baseline coefficient. We also note that large stocks allow for better market timing of large portfolio weight reductions.

Higher stock liquidity may limit the price impact of sell transactions.

The control variables show typically opposite signs for stock picking ability measured by the coefficients at the 90% and 95% quantile regressions. Funds with a large number of *Fund positions* are much better in stock selection if they decide to undertake a large portfolio weight increase. Since diversified funds are less likely to engage in large weight changes, any such exceptionally big portfolio modification may reflect private information and is indeed showing relatively better market timing. Large funds tend to be better stock pickers for very large portfolio weight increases at the 95% quantile, but for none of the quantiles below. Large stocks generally provide less opportunity for successful weight changes except at the extreme 5% quantile.

3.4.2 International versus Domestic Block Holders

Table 3.3, Panel B, also includes fixed effects for international funds, which are defined as those holding more than 10% of their portfolio share in foreign stocks. International funds can undertake portfolio weight changes in stocks headquartered in the country of the fund residence or they can modify portfolio weights for stocks other than their fund residence. We define a weight change dummy as *Home IF* or *Foreign IF*, respectively. International funds may have weaker relationships with the corporate officers in any particular country, particularly if the stock's headquarter is geographically remote. According to Hypothesis 3, we therefore expect a negative coefficient particularly for the 5% and 10% quantiles characterizing large portfolio weight reductions. The regression control in Table 3.3, Panel B controls for observable heterogeneity in fund size, stock size and the number of fund positions.

At the 5% quantile regression, the coefficient of the dummies as *Home IF* and *Foreign IF* are -0.447 and -0.851, respectively. Compared to the baseline coefficient of 1.549 in Panel A, this amounts to a 29% and 55% lower market timing ability for both fund types, respectively. Particularly geographically distant funds therefore show a much weaker ability for market timing in their large sell transactions which is both economically and statistically significant. On the other hand, the same funds are good stock pickers when it comes to large positive weight changes as is evident from the positive coefficients at the 90% and 95% quantiles. Interestingly, this stock picking advantage for international funds does not differ much as to the distance of the stock from the fund headquarter. The stock picking advantage of an international fund in foreign stocks at the 95% quantile is roughly of the same magnitude as disadvantage in stock liquidation at the 5% quantile of weight changes, namely 0.833 and −0.851, respectively.

3.4.3 Market Timing by Block Holding Size

Funds with large block holdings in a particular stock have particular incentives to solicit private information from company managers. If their holding share is also large relative to the stock market capitalization of the company, that is likely to give those funds more influence over management and potentially better access to private information. In this section we sort all fund positions changes into terciles according to original portfolio weight of the position (1 = small portfolio weights, 3 = large portfolio weights). In a second sort, we distinguish terciles sorted on a funds' original fund investment relative to a stocks' market capitalization (1 = small share holdings, 3 = large share holdings). This double sort yields nine buckets of portfolio weight changes ranging from (1,1) for small positions (both in terms of fund size and stock market capitalization) to (3,3) for large positions again relative to fund size and stock market capitalization. If block holdings in (3,3) are the source of inside information, then the market timing ability for position liquidations should manifest itself in this group much more than in (1,1).

Table 3.4 reports quantile regressions for portfolio weight changes at the 5%, 10%, 90% and 95% quantiles starting from small positions (1,1) and large positions (3,3), respectively. Panel A provides the results for the baseline regressions with the excess return ($ER(t+1)$) and a constant as the only regressors, whereas Panel B controls for the fund type, fund size, stock size and fund diversification characteristics interacted with the excess return. The quantile regressions for funds with large positions show again the S-shaped pattern from Table 3.3, Panel A, but more pronounced. The coefficient for the 5% quantile has increased to 4.641 relative to 1.549 in the full sample of all weight changes. By contrast, weight changes corresponding to smaller initial stock holdings relative to fund and stock size show no longer any ability for market timing in portfolio weight reductions at the 5% quantile. Both groups show negative timing ability for position increases at the opposite 95% quantile. Figure 3.5 provides the graphical illustration, where the coefficient plot as a function of the regression quantile shows an S-shaped pattern for large initial position (right graph), but not for funds which hold small positions (left graph).

3.5 Conclusion

In this article, we study the heterogeneity in market timing ability by mutual fund managers. Our results unravel an interesting pattern in the response of portfolio weight changes to future stock returns. First, we strongly reject the homogeneity of reactions of fund managers trades. Second, we show that the lower (higher) conditional quantiles estimates of change in past portfolio weights given the future stock expected returns are positive (negative), which is consistent with the existence of some *big winners* (*big losers*). Further evidence is found for the *winners-losers* pattern when we run quantile regressions in subsamples in which we restrict our observations to be only positive or only non-positive past change in portfolio weights or future stock excess returns: only the subsample with only non-positive past change in portfolio weights and the subsample with only non-positive future stock excess returns show a positive significant estimate, which is consistent with stock picking skills, suggesting winners are only associated to selling positions.

We then investigate whether the selling skills might be linked to insider information, which should be more relevant for funds that have important stakes at firms. We split again our sample, now into *large positions* and *small positions*, sorted by past portfolio weights and past institutional share of the firm's market capitalization. As expected, the quantile regression estimates in the *large positions* subsample show a more pronounced *winner-loser* shape than in the whole sample, while the ones in the *small positions* subsample are much flatter. This result suggests that large block holdings and large portfolio weights might be a source of insider information.

Finally, further tests reinforce the insider information mechanism might be a source of the superior skill for selling stocks. Consistent with previous studies, we find that international funds, in special their foreign positions, underperform domestic ones, as the acquisition of information gets harder the further the fund is from the corporation's headquarters.

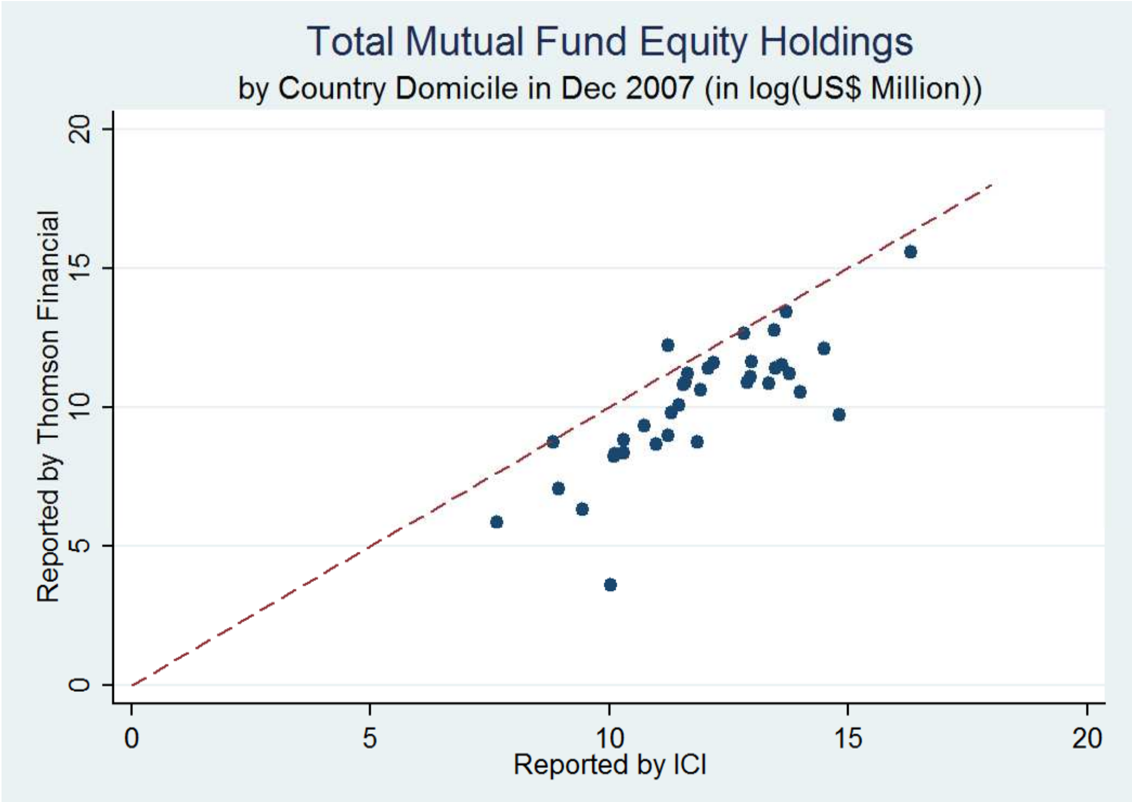


Figure 3.1: **Total net assets of mutual funds (in Log(US$ Million))**, aggregated by fund country domicile, in December 2007. The values reported come from two different sources: in the horizontal axis, the total value of equity positions of all funds by country domicile, according to Investment Company Industry (ICI) is shown; in the vertical axis, the total value of equity positions of all funds by country domicile, according to Thomson Financial is reported. The dotted line is a 45 degrees line.

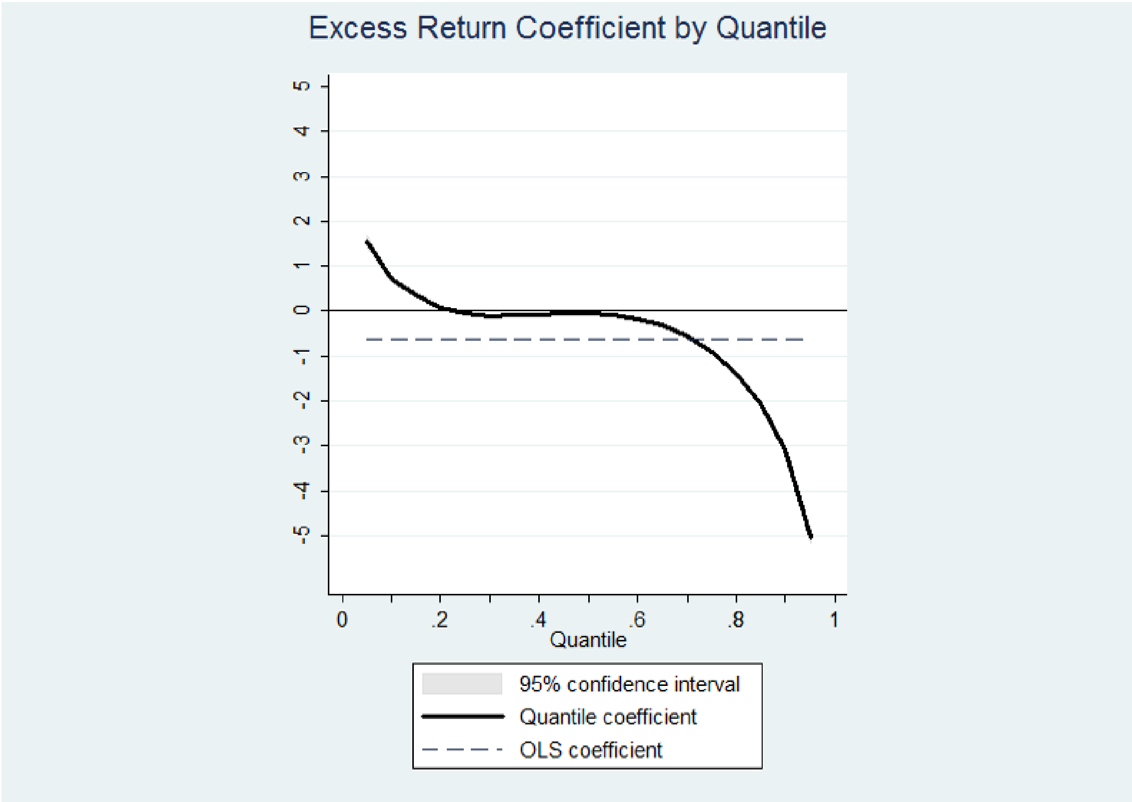


Figure 3.2: **Excess Return Coefficient by Quantile - Baseline Regression.** Plotted is the regression coefficient for excess return in a quantile regression which regresses the portfolio weight change (by quantile) in semester t on the excess returns in the consecutive semester $t + 1$.

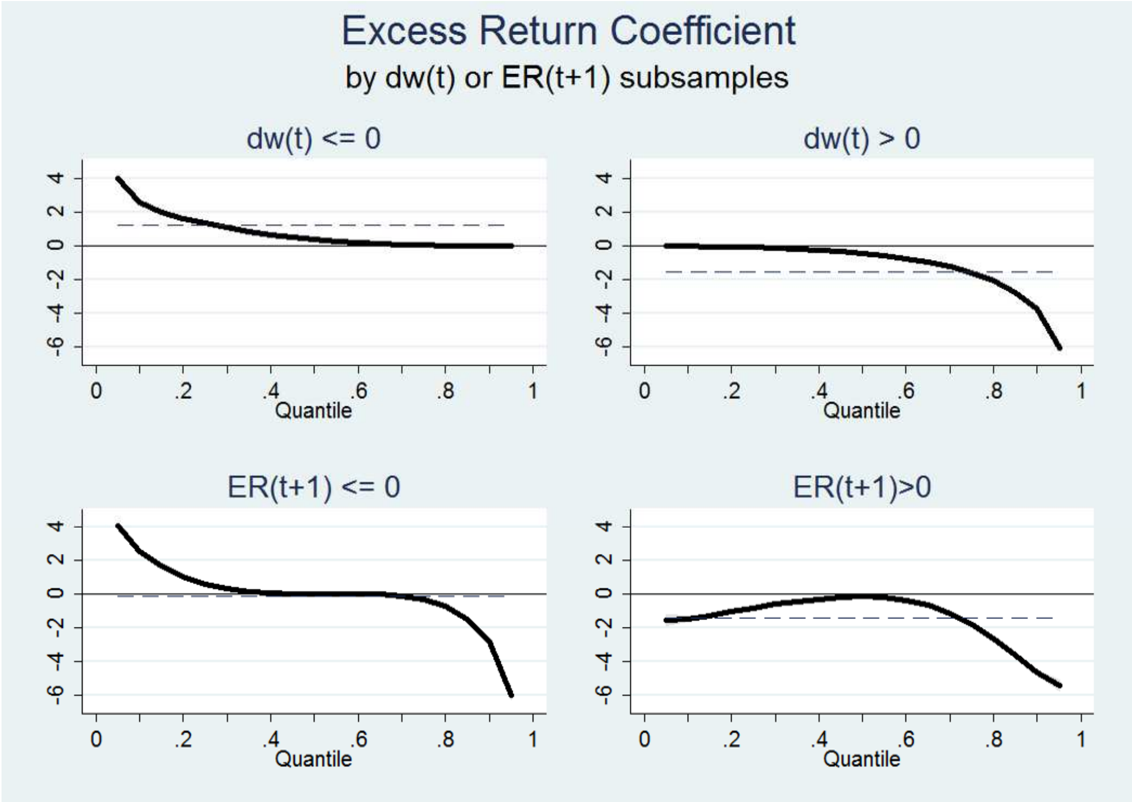


Figure 3.3: **Excess Return Coefficient by Quantile -** dw_t **or** ER_{t+1} **subsamples.** Plotted is the regression coefficient for excess return in a quantile regression which regresses the portfolio weight change (by quantile) in semester t on the excess returns in the consecutive semester $t+1$ for different subsamples. In the top left subsample, we restrict it to only non-positive portfolio weight changes observations. In the top right subsample, we restrict it to only positive portfolio weight changes observations. In the bottom left subsample, we restrict it to only non-positive future excess return observations. In the bottom right subsample, we restrict it to only positive future excess return observations. The solid line represents the quantile regression estimates. The dashed line represents the OLS coefficient estimate. The grey shaded area (which is almost invisible in this figure due to the higher significance of estimates) represents the 95% confidence interval.

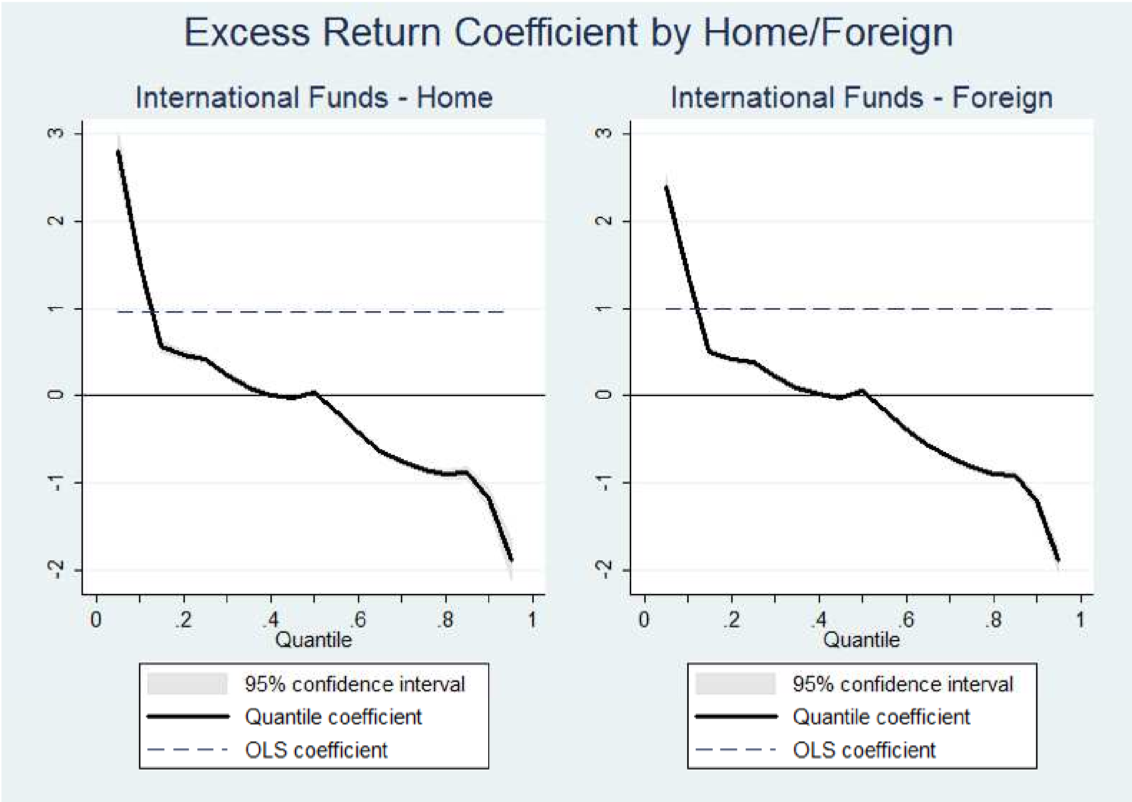


Figure 3.4: **Excess Return Coefficient by Quantile - International Home/Foreign Subsamples.** The regression coefficients for excess return in a quantile regression which regresses the portfolio weight change (by quantile) in semester t on the excess returns in the consecutive semester $t+1$ are plotted. The displayed estimates are: on the left hand side subplot international funds investing at home, and on the right hand side subplot international funds investing abroad.

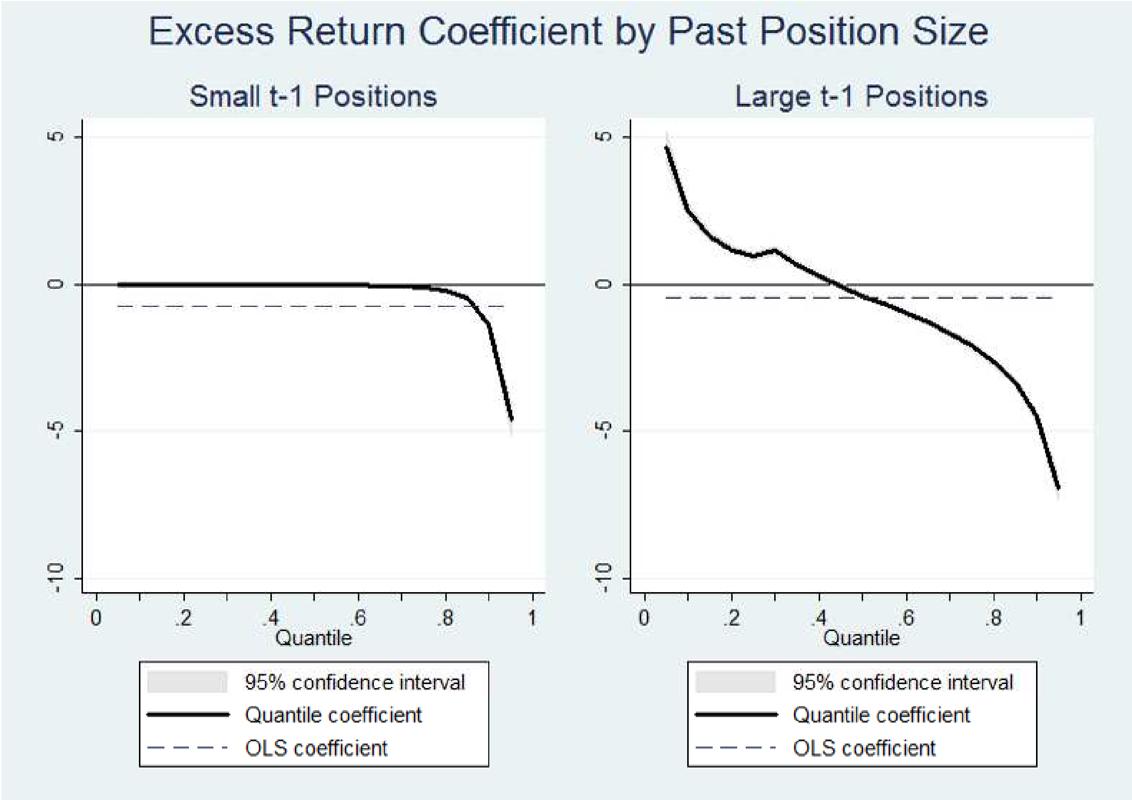


Figure 3.5: **Excess Return Coefficient by Quantile - Past Position Size Subsamples.** The regression coefficients for excess return in a quantile regression which regresses the portfolio weight change (by quantile) in semester t on the excess returns in the consecutive semester $t+1$ are plotted. The displayed estimates are on the left hand side subplot for a subset containing only the bottom tercile positions in semester $t-1$, and on the right hand side subplot for a subset containing only the top tercile positions in semester $t-1$. Positions have two dimensions and are sorted into terciles. The first dimension is the fund portfolio weight and the second dimension is the the share of the stock held by an individual fund. A small (large) position indicates the bottom (top) tercile in both dimensions.

Table 3.1: **Number and Size of Equity Mutual Funds by Fund Domicile**

This table presents the number of funds and total fund net assets value (in US$ Million) by fund domicile in December 2007. A fund is classified as international if it invests at least 10% of its assets abroad.

	All Funds		Domestic Funds		International Funds	
Fund Domicile	Number of Funds	TNA (US$ Million)	Number of Funds	TNA (US$ Million)	Number of Funds	TNA (US$ Million)
Argentina	50	6,280	3	1	47	6,280
Australia	151	38,200	94	27,500	57	10,600
Austria	125	6,170	12	1,420	113	4,760
Belgium	268	40,400	8	633	260	39,700
Bermuda	8	42,200	0	0	8	42,200
Brazil	699	52,000	696	50,100	3	1,980
Canada	999	354,000	450	115,000	549	239,000
Chile	110	3,850	38	1,780	72	2,070
China	137	112,000	137	112,000	0	0
Cyprus	2	17	0	0	2	17
Czech Republic	16	1,190	0	0	16	1,190
Denmark	228	50,000	16	2,510	212	47,500
Estonia	4	1,090	0	0	4	1,090
Finland	118	18,100	22	4,350	96	13,700
France	747	179,000	152	38,800	595	140,000
Germany	2,036	313,000	104	30,700	1,932	282,000
Greece	106	6,850	63	5,760	43	1,080
Hong Kong	153	101,000	0	0	153	101,000
Hungary	6	565	1	34	5	531
Iceland	2	179	0	0	2	179
India	276	53,300	267	42,000	9	11,400
Ireland	115	72,800	1	128	114	72,700
Italy	505	65,000	58	10,100	447	54,900
Japan	352	91,000	267	58,100	85	32,900
Latvia	3	11	0	0	3	11
Liechtenstein	62	4,120	0	0	62	4,120
Luxembourg	249	16,500	1	0	248	16,500
Malaysia	95	1,840	82	1,680	13	164
Mexico	92	7,980	65	6,280	27	1,700
Morocco	1	59	1	59	0	0
Netherlands	143	72,100	11	8,150	132	63,900
Norway	151	201,000	49	8,340	102	193,000
Philippines	5	346	5	346	0	0
Poland	48	11,400	26	4,510	22	6,870
Portugal	119	4,270	45	1,280	74	2,990
Saudi Arabia	1	248	1	248	0	0
Singapore	186	81,600	14	2,760	172	78,900
Slovenia	1	0	0	0	1	0
South Africa	118	23,700	25	3,880	93	19,800
Spain	3,189	53,900	452	11,300	2,737	42,600
Swaziland	2	37	0	0	2	37
Sweden	356	110,000	96	28,900	260	81,600
Switzerland	450	89,100	62	17,900	388	71,200
Taiwan, R.O.C.	96	5,890	93	5,750	3	132
Thailand	9	276	9	276	0	0
Turkey	2	37	2	37	0	0
United Kingdom	1,223	667,000	197	114,000	1,026	553,000
United States	5,482	5,710,000	3,155	2,610,000	2,327	3,100,000
Total	19,296	8,669,605	6,780	3,326,612	12,516	5,343,301

Table 3.2: **Summary Statistics on Regression Variables**

Reported below are the summary statistics. The change in weights from month t-6 to month t dw is multiplied by 1000 and can vary between -1000 and 1000. Raw returns are the stock returns between the current period and 6 months later. Risk adjusted excess returns are the stock returns between the current period and 6 months later controlled for risk factors. The risk adjustment is based on an eight factor international asset pricing model with the following factors: domestic market, domestic size, domestic value, domestic momentum, non-local market, non-local size, non-local value and non-local momentum. The non-local factors are factors averaged across all countries except the local one. The control variables are as follows: Home IF is the interaction of the dummy Home with the dummy International Fund. The dummy Home assumes value 1 only and if only fund and stock are located in the same country. The dummy International Fund assumes value 1 only and if only a fund invests more than 10% of its TNA in foreign stocks in a certain period. Foreign IF is the interaction of the dummy Foreign with the dummy International Fund. The dummy Foreign assumes value 1 only and if only fund and stock are not located in the same country. US IF, UK IF, Eurozone IF and Other IF are the US, UK, Eurozone and Other countries dummies interacted with the International Fund dummy, respectively. These country dummies assume value 1 only and if only the fund is located in the country to which the dummy refers to. US refers to the United States. UK refers to the United Kingdom. Eurozone refers to Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia or Spain. Other countries refer to all countries that are not the United States, the United Kingdom or one of the Eurozone countries. Fund Size is the Total net assets in dollars held by the fund in a certain period. Stock size is the total market capitalization in dollars of a stock in a certain period. Fund positions is the number of stock positions held by a fund in a certain period. All the listed control variables are also interacted with the risk adjusted excess returns to form new control variables. The sample contain half-yearly observations from 1999 to 2009.

Variable	Obs.	Mean	Median	STD	Min	p25	p75	Max
dw	8,335,057	-.00399	.001506	13.11	-1,000	-1.317	1.428	431.8
Raw returns	8,335,057	.03266	.05596	.2508	−.8841	−.08277	.1811	.8113
Risk adjusted (excess) returns (ER)	8,335,057	−.03463	.0003076	.278	−2.069	−.1657	.1315	.9143
Controls								
Home IF	8,335,057	.1576	0	.3644	0	0	0	1
Foreign IF	8,335,057	.5414	1	.4983	0	0	1	1
US IF	8,335,057	.1677	0	.3736	0	0	0	1
UK IF	8,335,057	.1019	0	.3025	0	0	0	1
Eurozone IF	8,335,057	.1518	0	.3589	0	0	0	1
Other IF	8,335,057	.1199	0	.3248	0	0	0	1
Fund Size	8,335,057	18.64	18.45	1.606	16.12	17.4	19.67	25.74
Stock Size	8,335,057	19.93	20.07	1.77	6.908	18.88	21.11	29.54
Fund Positions	8,335,057	4.941	4.682	1.255	1.792	3.912	5.948	8.487
Interacted Controls								
$Home\ IF \times ER(t+1)$	8,335,057	−.004178	0	.1075	−2.038	0	0	.9142
$Foreign\ IF \times ER(t+1)$	8,335,057	−.02045	0	.2046	−2.069	−.02438	.01924	.9143
$US\ IF \times ER(t+1)$	8,335,057	−.006003	0	.1157	−2.04	0	0	.9143
$UK\ IF \times ER(t+1)$	8,335,057	−.003736	0	.09176	−2.038	0	0	.9133
$Eurozone\ IF \times ER(t+1)$	8,335,057	−.006105	0	.1037	−2.038	0	0	.9143
$Other\ IF \times ER(t+1)$	8,335,057	−.004608	0	.09808	−2.069	0	0	.9133
$Fund\ Size \times ER(t+1)$	8,335,057	.1159	.368	4.62	−48.44	−2.122	2.722	30.97
$Stock\ Size \times ER(t+1)$	8,335,057	.1172	.3698	4.852	−47.99	−2.31	2.922	28.41
$Fund\ Positions \times ER(t+1)$	8,335,057	−.1633	.001391	1.416	−17.01	−.7835	.6211	7.744

Table 3.3: **Heterogeneity in Market Timing Ability**

Reported are quantile regressions in which institutional fund holding changes in a semester t (measured as changes in the portfolio shares) are regressed on a constant and the risk-adjusted excess return (ER) in semester $t+1$. For each quantiles ($q = 5\%, 10\%, 25\%, 75\%, 90\%$ and 95%) we report a specification with and without control variable. *Home IF* denotes a dummy for a holding change by an international fund for which the stock (main) trading location and the fund incorporation are in the same country, whereas *Foreign IF* denote a dummy for holding changes of international funds which are located in countries other than the main trading location of the stock. International funds (IF) are defined as those with at least 10% of their portfolio share in stocks traded outside their country of incorporation. *Fund Size* represents the aggregate value of the fund's equity portfolio (measured in log of millions of U.S. dollars), *Stock Size* denotes the market capitalization of the stock (measured in log of millions of U.S. dollars), and *Fund Positions* measures (in logs) the number of the fund's equity positions. In the extended specification, all control variables are included as interacted with the excess return ($\times ER(t+1)$) and as well as non-interacted terms (not reported). Standard errors are provided below the estimates.

Panel A: Unconditional Specification

	Quantile Regressions							OLS
	5%	10%	25%	50%	75%	90%	95%	
Constant	-15.569***	-8.022***	-1.852***	-0.074***	2.041***	8.601***	15.396***	0.05
	[0.296]	[0.14]	[0.037]	[0.012]	[0.048]	[0.125]	[0.258]	[0.068]
$ER(t+1)$	1.549***	0.731***	-0.059***	-0.039***	-0.903***	-3.094***	-5.029***	-0.625***
	[0.06]	[0.033]	[0.006]	[0.002]	[0.007]	[0.036]	[0.069]	[0.018]
Level Controls	No	No	No	No	No	No	No	No
Obs.	8,335,057	8,335,057	8,335,057	8,335,057	8,335,057	8,335,057	8,335,057	8,335,057

Panel B: Conditional Specification

	Quantile Regressions							OLS
	5%	10%	25%	50%	75%	90%	95%	
Constant	-34.983***	-22.346***	-7.811***	-0.19***	6.201***	19.893***	35.436***	-1.622***
	[0.169]	[0.103]	[0.033]	[0.018]	[0.036]	[0.097]	[0.189]	[0.111]
$ER(t+1)$	3.237***	2.049***	0.56***	0.022	-1.196***	-1.944***	-2.71***	0.914***
	[0.338]	[0.173]	[0.07]	[0.039]	[0.074]	[0.18]	[0.383]	[0.239]
Interacted Controls								
$Home\ IF \times ER(t+1)$	-0.447***	-0.515***	-0.141***	0.021**	0.351***	0.779***	0.829***	0.052
	[0.11]	[0.048]	[0.018]	[0.009]	[0.019]	[0.053]	[0.117]	[0.047]
$Foreign\ IF \times ER(t+1)$	-0.851***	-0.652***	-0.181***	0.03***	0.384***	0.745***	0.833***	0.085**
	[0.063]	[0.031]	[0.011]	[0.006]	[0.012]	[0.033]	[0.07]	[0.035]
$Fund\ Size \times ER(t+1)$	-0.076***	-0.019***	0.008***	-0.002	-0.001	-0.009	0.05***	0.021**
	[0.01]	[0.006]	[0.002]	[0.001]	[0.002]	[0.007]	[0.012]	[0.01]
$Stock\ Size \times ER(t+1)$	0.041***	-0.016***	-0.018***	-0.017***	-0.091***	-0.174***	-0.28***	-0.158***
	[0.011]	[0.006]	[0.002]	[0.001]	[0.002]	[0.006]	[0.013]	[0.008]
$Fund\ Positions \times ER(t+1)$	-0.198***	-0.089***	-0.03***	0.04***	0.346***	0.58***	0.737***	0.221***
	[0.017]	[0.009]	[0.005]	[0.003]	[0.005]	[0.011]	[0.022]	[0.013]
Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,480,047	8,480,047	8,480,047	8,480,047	8,480,047	8,480,047	8,480,047	8,480,047

Table 3.4: **Market Timing Ability by Position Size**

We repeat the quantile regressions in Table 3.3 for two subsamples of large and small positions. Fund holdings at the beginning of period t are sorted into three equal size terciles based their size (i) relative to the fund capitalization (fund position size) and (ii) relative to the stock capitalization (stock position size). All positions which are in the large size group by both sorts are labeled "Large Positions" and those which are in the small group by both sorts are labeled "Small Positions". Separate quantile regressions are reported for both subsamples with and without the controls described in Table 3.3. Standard errors are provided below the estimates.

Panel A: Unconditional Specification

	Quantile Regressions							
	Large Positions				Small Positions			
	5%	10%	90%	95%	5%	10%	90%	95%
Constant	-27.403***	-16.491***	11.991***	22.861***	-0.414***	-0.299***	0.911***	3.618***
	[0.94]	[0.449]	[0.403]	[0.867]	[0.009]	[0.012]	[0.03]	[0.247]
$ER(t+1)$	4.641***	2.513***	-4.499***	-6.909***	-0.023***	-0.017***	-1.364***	-4.598***
	[0.269]	[0.127]	[0.112]	[0.204]	[0.002]	[0.002]	[0.071]	[0.284]
Level Controls	No	No	No	No	No	No	No	No
Obs.	1,158,675	1,158,675	1,158,675	1,158,675	1,232,495	1,232,495	1,232,495	1,232,495

Panel B: Conditional Specifications

	Quantile Regressions							
	Large Positions				Small Positions			
	5%	10%	90%	95%	5%	10%	90%	95%
Constant	-76.391***	-51.207***	36.194***	59.187***	-2.012***	-1.328***	33.108***	60.742***
	[1.102]	[0.499]	[0.445]	[1.071]	[0.016]	[0.019]	[0.926]	[0.565]
$ER(t+1)$	12.233***	6.99***	0.561	-0.272	0.26***	0.172***	-0.803	-1.162
	[2.259]	[1.106]	[0.972]	[1.966]	[0.036]	[0.041]	[0.522]	[0.753]
Interacted Controls								
$Home\ IF \times ER(t+1)$	-0.596	-0.825***	0.516**	0.121	-0.016*	0.008	0.366**	1.163***
	[0.719]	[0.306]	[0.252]	[0.556]	[0.008]	[0.009]	[0.185]	[0.326]
$Foreign\ IF \times ER(t+1)$	-3.187***	-1.818***	1.31***	2.323***	-0.004	0.008	0.571***	1.247***
	[0.474]	[0.205]	[0.183]	[0.387]	[0.005]	[0.007]	[0.156]	[0.308]
$Fund\ Size \times ER(t+1)$	-0.268**	-0.105	-0.367***	-0.435***	0.002	0.001	0.024	-0.125***
	[0.135]	[0.066]	[0.06]	[0.125]	[0.002]	[0.002]	[0.016]	[0.022]
$Stock\ Size \times ER(t+1)$	0.023	0.018	-0.26***	-0.256***	-0.011***	-0.007***	0.045***	-0.006
	[0.081]	[0.045]	[0.042]	[0.087]	[0.001]	[0.001]	[0.014]	[0.017]
$Fund\ Positions \times ER(t+1)$	-0.67***	-0.611***	1.746***	1.735***	-0.016***	-0.01***	-0.174***	0.282***
	[0.188]	[0.105]	[0.099]	[0.166]	[0.003]	[0.003]	[0.045]	[0.078]
Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,158,675	1,158,675	1,158,675	1,158,675	1,232,495	1,232,495	1,232,495	1,232,495

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