ESSAYS ON INFORMATION ASYMMETRIES AND AGENTS' BEHAVIOR IN THE FINANCIAL SECTOR

By

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I would like to thank my mom, sister and husband.

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This dissertation consists of three main chapters. The first chapter examines the impact of the quality of information that lenders gather about potential borrowers on interest rates. Banks observe private signals and price to borrowers according to a previously announced pricing policy. An equilibrium is found in price policy functions.

This chapter shows that efficiency can be achieved more easily in markets where different lenders specialize in specific types of borrowers with whom they have a considerable informational advantage. On the other hand, more symmetric markets allow for higher profits for the lender with an informational disadvantage.

The second chapter analyzes both endogenous bank preference formation and lender switching problems in the context of an optimal stopping problem. The model is developed around a group of safe and risky borrowers that search for a lender to finance a particular project. Depending on the rentability of the projects and the differences in projects' risk, borrowers select a bank. Low quality signals generate pooling equilibria where either low risk projects subsidize high profits of risky projects, or

only risky projects are funded in early periods. High quality signals on the other hand generate more efficient markets.

The third chapter's main goal is to analyze analysts' coverage of stocks. Here an empirical study estimates the relationship between coverage and the informational environment of a firm. Coverage seems to decrease on average with higher errors in estimation. The data also shows that physically large firms experience a resistance of their coverage to get reduced. Higher past revisions also decrease coverage showing a real cost of uncertainty. Finally, evidence suggests that firms with higher market value have lower probabilities to have their coverage increased.

CHAPTER 1
IMPORTANCE OF QUALITY OF INFORMATION IN PRICING, MARKET STRUCTURE AND EFFICIENCY: THE CASE OF BANKING

Introduction

This chapter examines the impact of the quality of information that lenders gather about potential borrowers on interest rates, the structure of the lending market, and its efficiency.

The asymmetry to which this chapter refers to is in the accuracy of the predictions about borrowers' ability to pay given by the signals each lender observes. Sharpe (1990) developed a model of lending with similar set up of asymmetric information where the interest rates offered to borrowers were made simultaneously. He finds a Nash Equilibrium in pure strategies for the offers. Von Thadden (2001) contested these results by arguing that there is no Pure Strategy Nash equilibria in that game[1]. In fact, Hauswald and Marquez (2003) note that "the result that no pure strategy equilibrium exists when bidders have asymmetric information is standard" (p. 927). Due to the more realistic properties and clear predictions of pure equilibria (it is unlikely that private institutions randomize their pricing policies in practice), this result is rather upsetting. This chapter shows that a change of the setting of the model towards a more realistic assumption where an equilibrium is found in price functions, instead of specific values, has a pure Nash equilibrium and gives a prediction for the market interest rates. In addition, this chapter expands previous literature by pointing out that informational advantage creates different market structure consequences depending on the

[1] Hauswald and Marquez (2003) and Rajan (1992) developed similar models based on Sharpe (1990) where no Pure Nash equilibria exists.

dimension of the asymmetry. An equilibrium is described for each of the cases and some policy implications regarding the efficiency of the lending markets are discussed.

Whether bank competition is desirable and how this market structure is affected by information asymmetries has been and continues to be a lively topic of research[2]. This chapter of my dissertation contributes to this literature by expanding our understanding of the nature of banking competition and its consequences on the efficiency of the allocation of financial resources. Allocating money to the least risky individuals cheaper sends an appropriate signal to borrowers and rewards those who have the most chance of paying back. This is particularly important after the 2008 crisis in the financial sector generated in part by huge amounts of non-performing loans.

The effects of different information quality in a market have been examined in industries other than banking. For example, auction theory has examined the changes that arise in equilibrium from the change in the quality of the information when all but one participant can observe the same signal (Kagel and Levin 1999). Further, Lundberg and Startz (1983) analyze the case of symmetric companies receiving signals of different qualities for workers from different groups of society. This chapter is different from the last mentioned paper in that when asymmetric information is analyzed here, the asymmetry arises among lenders, but not necessarily among the borrowers. In other words, the quality of the information does not depend here on the type of borrower.

It will be shown that, given that the best the market can do is to categorize according to best existing technology, there is a greater probability of that happening when there is specialization in the market. Ironically, more symmetric markets tend to

[2] See Ariccia et al. (1999), Guzman (2000) and Cao and Shin (2001).

have more “bad” borrowers getting the best offers while some “good” ones, as determined by the best technology in the market, have to pay higher interest rates.

The chapter proceeds as follows. Section two will develop a discrete model of asymmetric information in the lending market. Section three explains the equilibrium concept for the model in section two. Section three present the equilibrium. Section four concludes with some policy implications and future research ideas. All proofs will be explained in detail in the appendix.

The Model

There are two lenders and several borrowers (indexed by *k*) in the model. The lenders have access to a technology that provides a costless assessment of the credit worthiness of each borrower. The technology of one lender (*i*) more accurately categorizes borrowers than does the technology of the other lender (*j*)[3].

There are two types of borrowers defined by their ability to pay. A fraction of them (θ) will be able to pay back the loan up to an amount V. The rest of the borrowers (1-θ) will be unable to pay back any amount. Just as in Sharpe (1990) each borrower learns about its own type after the loan is made.

Following previous literature[4], let there be two signals about the credit worthiness of each borrower: high and low. Let p_{qm} be the probability that when lender *q* observes signal *m* the borrower is of type *m* (for *m=h,l*). A type *h* borrower can pay back the loan up to V (and so is a “good” borrower). A type *l* borrower is unable to pay back the loan

[3] Hauswald and Marquez (2003) suggest a lender would incur costs to avoid losing its informational advantage, and the amount of effort to avoid spillovers would depend on the dissemination of information in a market. I will focus on the effects of quality of information given the informational (dis)advantage.

[4] Sharpe (1990), Von Thadden (2001), Vesala (2007).

(and so is a “bad” borrower). The signal *h* refers to a *h*igh probability of paying back, and will be referred to as a “high” signal; *l* will be referred to as a “low” signal.

The expected profit of lender *q* upon observing signal *m* is:

$$\pi_{mq} = r * \Pr(V_k = h | S_q = m) - 1 * [1 - \Pr(V_k = h | S_q = m)] \qquad (1\text{-}1)$$

where S_q refers to the signal observed by lender q, V_k is borrower k’s type , r is the interest rate and the amount of the loan is normalized to one.

Definition 1: The term accuracy in my entire work has the following interpretation: Si is more accurate than Sj if $\Pr[V_k = S_i | S_i] > \Pr[V_k = S_j | S_j]$. According to this definition of accuracy, a lender’s signal is more accurate than the competitor’s one if $p_{ih} > p_{jh}$ and $p_{il} > p_{jl}$. It is possible that a lender has a more accurate signal given that he observes high, but that the signal is less accurate than the competitors’ given that he observed low (that only one inequality holds). For the purposes of this chapter such a case will not be developed, although the equilibrium dynamics would be very similar as is explained later in the chapter.

Structure of the Game

The accuracy of each lender’s signal is assumed to be common knowledge. Define a pricing policy as the set of interest rates that each lender offers. Each lender observes only its own signal and the strategy of its competitors, and so the interest rate that a lender specifies varies only with this information. Then, a pricing policy of a lender consists of the interest rate that the firm will offer to the borrower upon observing a low signal, and the corresponding interest rate that the firm will offer when it observes a high signal. Pricing policies are public, so that lenders announce their policies before borrowers approach them[5].

Let time be continuous and borrowers can apply for a loan at any random point in time. So lenders do not know when an application will arrive. Lenders must define their pricing policies before borrowers apply for loans; they will commit to a function instead of a price value[6]. In other words, each bank will announce, or publicize, the interval of interest rates that it will charge in the coming period. The purpose of this setup is to eliminate the possibility of banks randomizing their policies, in other words, I am eliminating the option of banks changing the interest rate assigned to each borrower according to a probability function but they have to decide on a policy apriori. This is much as it happens in practice[7], banks do publicize some of their interest rates policies and one may assume that a policy of randomization would call the attention of regulators if it were to occur in practice. In addition, equilibria in price functions “allow a firm to adapt better to the uncertain environment” and it dramatically reduces the set of equilibria.[8] Klemperer and Meyer (1989) have a discussion on the benefits of analyzing supply function equilibria instead of a price-quantity point equilibria.

Equilibrium Concept

Take the following definitions:

[5] Sharpe (1990) makes a similar assumption. In pp 1076 he says: “[outsiders] observe the lending policies of their bank[the insider], but not individual offers.”

[6] The formal definition of this function is found in the next section: The Equilibrium Concept.

[7] In practice firms do not fix prices and leave them unchanged when the competitor changes its behavior. We observe retailers, for example, making new sales and changing prices as competitors decide to cut prices, or create loyalty accounts, etc.

[8] Klemperer and Meyer (1989). Pg.1244.

N is the number of possible states of nature. In this case, two, borrower of type H and borrower of type L.

Ω is a vector where each entry is a different state of nature, here (H,L).

Θ(Ω): Ω→ R^n. Θ(Ω) takes Ω and assigns a real value to each state of nature. Θ(Ω) is a vector that belongs to R^n. In the context of this study, each real value is the interest rate offered upon observing a particular realization of the signal.

f(θ): $R^n \rightarrow R^n$ is a function that takes a vector Θ(Ω) and assigns to it a new vector of real numbers. It can be interpreted as a response function to the pricing policy Θ(Ω). Let g(θ) be another such function.

$U_i(s, \mathrm{f}(\theta), \Theta(\Omega))$ is the expected profit of lender *i* on any particular borrower as a function of the observed signal (s), the offer made to each borrower, and the offers made by the competitor.

[f(θ),g(θ)] is an equilibrium in pricing policies if

Given a function g(θ); f(θ) maximizes U_i[s, f(θ),θ^*(Ω)] such that θ^*(Ω)=g(f(θ)) ∀θ

and

Given a function f(θ); g(θ) maximizes U_j[s, g(θ),θ^*(Ω)] such that θ^*(Ω)=f(g(θ)) ∀θ.

The prediction of the model, denominated here as the observed prices, is the set {θ_1, θ_2} to which {f_{i+1}(g_i(θ)), g_i(f_i(θ))} converge for any initial θ (if there is such a limit). Note that {θ_1, θ_2} may not be a Nash equilibrium in prices since f(θ) is a best response that maximizes U_i[s, f(θ),θ^*(Ω)] where the set of prices θ^*(Ω) are not fixed as in a Nash equilibrium, but are a function of f(θ). The same applies to g(θ). The resulting profit function may be greater, or smaller, than in a Nash Equilibrium in prices, depending on the specific problem.

Although it might seem like a strong assumption the modeled ability of lenders to observe the interest rate policy offered by their competitors and to adjust their own interest rates in response, recall that most banks advertise some of their interest rates policies at their offices or through media advertising and the internet, and that the increasing scrutiny in bank lending practices makes some of their actions publicly available.

After a pricing policy function is defined, when the borrowers apply for loans to all banks, each lender observes a signal, then interest rate offers are made simultaneously and independently based on the signal observed such that profits are greater than or equal to zero[9]. Each borrower will accept the lowest interest rate from among those offered by the lenders.

Thus, the model has the following timing:

Stage 1 is a game in pricing policies. Each lender finds an equilibrium function as defined above that determines interest rates offers according to the borrower's signal.

In stage 2 borrowers apply for loans to all banks and lenders make their offers simultaneously. The offer will be dictated by the pricing function specified in stage 1.

Borrowers accept the lowest interest rate from among the rates offered by the lenders. If the two lenders offer the same interest rate, the borrower randomly selects a lender.

Note that the policies, but not the outcome of the signal, can always be observed by all lenders. Notice too that profits will not be earned until a price structure has been

[9] It could also be considered the case of profits greater than or equal to *rl,* where *r* is the interest on some safe investment or the cost of lenders to get the capital, but the conclusions would be the same. For simplicity I will assume *r=0.* As will be addressed latter, if profits could not be made positive, no offer will be made. This occurs if it is almost certain that the borrower if of type *l.*

set, hence banks have an incentive to find some equilibrium in stage 1 (interest rate offers).

Let $r_q^0(m)$ be the interest rate at which the expected profit of lender *q*, described in Equation 1-1, is zero given that he observed signal *m*. Then,

$$r_q^0(L) = \frac{p_{ql}}{1-p_{ql}} \quad q = i, j$$

$$r_q^0(H) = \frac{1-p_{qh}}{p_{qh}} \quad q = i, j.$$

Given the definition of accuracy presented in *Definition 1*,

$$r_i^0(H) < r_j^0(H) \leq r_j^0(L) < r_i^0(L).$$

Equilibrium

The possible equilibria depend on whether the following inequality holds.

$$\frac{r_j^0(H) - r_i^0(H)}{r_j^0(L) - r_i^0(H)} > \Pr(S_j = L | S_i = H) \tag{1-2}$$

The equation can also be written as $[r_j^0(H) - r_i^0(H)] > \Pr(S_j = L | S_i = H) * [r_j^0(L) - r_i^0(H)]$. The left hand side corresponds to the premium lender *i* can charge to borrowers from whom a high signal is observed given the existence of the less accurate lender, if its offer is $r_j^0(H)$. The right hand side corresponds to the same premium but if the offer is $r_j^0(L)$. The probability term on the right hand side is necessary because such an offer will only be considered if J observes low. The reason why these particular premiums are compared will become evident after Propositions 1 and 2, and is explained in detail in its proof.

The left hand side is decreasing in $r_i^0(H)$, which increases as *i* becomes less accurate, and approaches one (increases) as $r_j^0(H)$ gets closer to $r_j^0(L)$, which occurs when *j* becomes less accurate. Hence, the left hand side increases as both lenders differ more in their accuracy. The following table shows an example of when 1-2 holds and when it does not.

Table 1-1. Numerical example

θ=		0.5		
p_{ih}=p_{il}	p_{jh}=p_{jl}	LHS[10]	Pr(L|H)	1-2 holds
0.62	0.6	0.0606	0.476	NO
0.85	0.6	0.3704	0.43	NO
0.9	0.55	0.6364	0.46	YES
0.85	0.8	0.0192	0.29	NO

When (1-2) does not hold, the probability that the lender with the informational advantage observes the high signal and the competitor observes the low signal is sufficiently high that the first one will not mind losing some of the good borrowers because it can charge a high interest rate to those who are potentially categorized incorrectly by the other lender and make high expected profits on these low-risk customers. Remember that the lender with an informational advantage is more accurate at categorizing the good borrowers.

Proposition 1: The following is an equilibrium of this game when (1-2) holds: The lender with an informational advantage will implement the policy $r_i^*(H) = r_j^0(H),\ \ r_i^*(L) = r_i^0(L)$, and the competitor will set the policy $r_j^*(H) = r_i^0(L)$, $r_j^*(L) = r_i^0(L)$[11].

[10] Left hand side of Equation (1-2).

[11] This result is similar to Sharpe (1990), but in this case each lender conditions its offer only on its own signal. The complete conditional strategies are in the appendix as part of the proof. Here are stated the observed final prices.

The lender with the most accurate signal will offer an interest rate that sets its expected profit equal to zero when the signal is low. When its signal is high the offer will be such that the other lender would always have zero expected profits if it observed a high signal. The lender with the worst signal will have only one interest rate, and this will be the same as the offer made by the most accurate lender when it observes low signal.

In this equilibrium, the lowest interest rate is offered only to those who get a high signal from the most accurate lender. In this sense, the market is as efficient as its technology allows it to be[12].

Note that if p_{il} goes to one, then $r_i^0(L)$ would increase until the risk of default given that the signal is low is so certain that no offer will be made. Assume for simplicity that this does not happen[13]. In fact, any *r* must be less than or equal to *V-1* or default is certain and no offer is made upon observing low. On the other hand, upon observing the high signal the lender with the informational advantage can charge a premium over the rate that guarantees zero profits, which allows him to get positive profits[14].

In this equilibrium, the competitor will make zero profits and only lends to borrowers for whom *i* observed L. However, it might still earn positive profits in the lending market if it holds an informational advantage with respect to a different type of borrowers than the ones modeled here. There could be different types of borrowers (young professionals vs. experienced professionals, international vs. domestic borrowers, etc.) with lenders' accuracy being the best for only one type. Then, lenders

[12] Remember efficiency here refers to the ability to correctly categorize borrowers.

[13] Formally, assume $p_{il} \leq (V-1)/V$.

[14] $r_i^*(H) > r_i^0(H)$

would specialize in whatever they do best and we would observe two separate markets with their respective set of interest rates.

With specialization I do not mean a lender focusing in the riskiest borrowers and another in the less risky borrowers, but rather specialization in separate markets such as international vs. domestic borrowers, borrowers from particular industries, or in loans for particular purposes[15].

Proposition 2: The equilibrium when (1-2) does not hold and the signals do NOT have the same accuracy is the following: The lender with an informational advantage will implement the policy $r_i^*(H) = r_j^0(L),\ \ r_i^*(L) = r_i^0(L)$. The competitor will implement the policy $r_j^*(L) = r_i^0(L), r_j^*(H) = r^*$for r^* such that $\frac{r^* - r_i^0(H)}{r_j^0(L) - r_i^0(H)} = \Pr(S_j = L|S_i = H)$[16].

When (1-2) does not hold, the lender with an informational advantage can afford to make loans to fewer good borrowers. The competitor, by having less information, is forced to compete more aggressively by charging the lowest interest rate in the market to those for whom it observes a high signal. This observation might help to explain why bigger lending companies can charge higher interest rates, if you are willing to assume they are information advantaged. Note that the existence of this equilibrium depends on a high probability that the competitor gets a low signal when the lender with the most accurate signal observes high. This is closely related to the probability that good borrowers get categorized correctly only by the lender with the advantage; these are the

[15] An analysis on the evidence of specialization in the market and other possible explanations for its existence is done by Carey, Post and Sharpe (1998).

[16] If $p_{iH} > p_{jh}\ but\ p_{jl} > p_{il}$, the equilibrium is the same in the sense that it is determined by the second and fourth highest interest rate in (1-1) proposition 1 and by the two highest in proposition 2. i.e. Under this scenario the order of (1-1) is different, but the second and fourth highest interest rate constitute the equilibrium when (1-2) holds in the same fashion as described here. The analogous statement is true when (1-2) does not hold. Since the proof is so similar to the one given for this proposition, it is omitted from the paper.

borrowers that get "exploited" or charged a higher interest rate than their counterparts who have $S_j = h$[17].

This equilibrium takes into account the fact that, as mentioned by Flannery (1996) and Kagel and Levin (1999), when one lender has better information, only the other lender needs to take into account the winner's curse. In this case, only *j* will worry when he observes a good signal that under a better estimation the borrower might actually be "bad". The lender with an advantage does not have any better or equal quality estimator to compare with, besides the unknown truth.

In the case of both lenders having the same accuracy given a high signal, (1-2) can clearly not hold since the left hand side will equal zero ($r_i^0(H) = r_j^0(H)$). Here, the lender with the informational advantage is the one with the highest accuracy given low is observed. It is important to note that neither of the cases analyzed here include the case of completely symmetric lenders. If $p_{ih} = p_{jh}$ and $p_{il} = p_{jl}$, *proposition 2* is NOT valid, even though (1-2) does not hold. The reason for this is that in that case the equilibrium predicts $r_i^*(H) = r_j^0(L) = r_i^0(L) = r_j^*(L) = r_i^*(L)$, which implies that, in contrast to what happens in the asymmetric case, those for whom S_j=L *and* S_i=H would randomly decide either lender[18], offering a slightly lower interest rate given high is observed would increase profits of lender I (note that since there is no "informational advantage," then the first player would be determined randomly). Since this case does not correspond to one of asymmetric information, it is only important here to note that for the equilibrium described here to hold, some asymmetry, even if very small, must

[17] $r^* \leq r_j^0(L)$

[18] In the asymmetric case all such borrowers accept i's offer (the lender with the informational advantage) as it is smaller than the competitor's one.

exist in the market[19]. An equilibrium such as the one described in Von Thadden (2001) applies to this case.

Comparison of the Possible Market Equilibria

For (1-2) to hold the differences in accuracy given that a high signal is observed must be relatively large. As mentioned above, if $p_{ih} = p_{jh}$, then $r_i^0(H) = r_j^0(H)$ and (1-2) would never hold. Hence, we can refer to the case when condition (1-2) holds as the case of a more asymmetric market. If the competitor is more accurate when categorizing the good borrowers of another market (international vs. domestic borrowers, poor vs. rich, etc.) then we can argue that it is also a more specialized market.

In the case of a more specialized, or asymmetric, market, lending is more efficient, but the lowest interest rate are smaller than when (1-2) does not hold. The profits of the most accurate lender determine the prevailing case i.e. (1-2) holds if and only if the profits of the most accurate lender are higher under the equilibrium in a specialized, or asymmetric, market than under the symmetric one. This follows from the fact that profits for the accurate lender are made only from those for whom the signal is high. In the equilibrium when (1-2) holds, only those borrowers for whom lender I, the one with the advantage, observed a high signal get the lowest interest rate. Then, the most accurate signal is being used to determine who gets the different offers. In the less specialized market, when (1-2) does not hold, more of the bad borrowers are getting the lowest interest rate since this is offered by the lender with an informational disadvantage (the

[19] The equilibrium of the completely symmetric case requires the assumption of bounded rationality where individuals use up to a maximum number of decimals. So that $r_i^*(H)$ equals the now existent maximum number less than $r_i^0(L)$.

competitor). The highest interest rate in the market is accepted only when all lenders observe a low signal, which is less often than in the more specialized case. In conclusion, the more symmetric market uses a combination of all signals to determine who gets what offer, which reduces efficiency and, as explained later, can be expected to have higher average interest rates.

Let Pr(S_i=*h*) = A and Pr(S_j=*h*) = B.

Where, $A = \frac{p_{il} - (1-\theta)}{p_{ih} + p_{il} - 1}$ and $B = \frac{p_{jl} - (1-\theta)}{p_{jh} + p_{jl} - 1}$.

Note that the probability of observing a high signal is increasing in the accuracy of the signal given a *l* is observed (increasing in p_{il}) and decreasing in the accuracy given a high observation (decreasing in p_{ih}).

The profits of the competitor are zero in the more specialized market, while they can be positive in the other market. In particular, profits of the lender with an informational disadvantage are $B\left(r^* - r_j^0(H)\right)$ while those of a lender with the advantage are less than $\Pr(S_j = L, S_i = H)\left(r_j^0(L) - r_i^0(H)\right)$ in the less specialized market. The higher the accuracy advantage of the first player, while (1-2) still not holding, the higher its profits. In both markets, profits for the first player are positive.

The average interest rate in both cases also depends on the particular values of A and B, the probabilities that each lender observes a high signal given accuracy. In the specialized market the average offer is $A * r_j^0(H) + (1 - A) * r_i^0(L)$ while in the less differentiated market it is $B * r^* + (1 - B) * A * r_j^0(L) + (1 - B) * (1 - A) * r_i^0(L)$.

Surprisingly, the average offered rate can be expected to be higher in the more symmetric market. This happens since a high probability of the lender with the advantage observing high (A high) and a low one for the competitor (B low) implies the first player can exploit more borrowers and hence we can expect (1-2) not to hold and the average rate in this market to be high .

Conclusion

Policy Implications

Since 2007 and 2008 the US economy has being facing a tightening in the credit market and great concerns have arisen that borrowers lent beyond their capacities. One would think that this could have been avoided with a better system of categorizing borrowers. The problems that the US is facing in its financial markets would be smaller in effects, or inexistent, if the market could perfectly categorize borrowers. Given that this is not possible, the best the market can do is to categorize according to best existing technology. As has been noted in this chapter, there is a greater probability of that happening when there is specialization in the market. When the lender with an informational advantage is “better enough” (so that (1-2) holds) than the competitor, the best signal available will be used to determine who gets the loans at the most beneficial terms. Ironically, more symmetric markets tend to have more “bad” borrowers getting the best offers while some “good” ones, as determined by the best technology in the market, have to pay higher interest rates.

In conclusion, efficiency can be achieved easier in markets where different lenders specialize in specific types of borrowers with whom they have a considerable informational advantage.

On the other hand, more symmetric markets allow for higher profits for the competitor. The lender with the informational advantage will determine which case is observed depending on where its own profits are greater.

This model may also be used to analyze the effects of direct government lending if we assume the government has less accurate information than the private sector and is interested in minimizing losses from the intervention. In this case the private sector would be *i* and the government *j*. According to the conclusions above, the government will either affect negatively the efficiency of the private signal in categorizing borrowers, if its quality is close to the private sector's, or it will lend only to the "worse" borrowers in the market, if it is sufficiently worse.

Future Research

There are some areas of research not explored in full that could be applied to extend the analysis in this chapter. In particular, little has been said about the consequences of the existence of technologies that improve the qualities of a signal.

One drawback of the model presented here is its lack of dynamics. The analysis here is a static one. This is no different than most of the previous literature, some of which has similar games with two or three states (Rajan 1992), but the extra periods are used to analyze other problems such as introducing borrower's effort. Introducing infinite time periods where reputation and loyalty to a "business partner" play a role could enrich considerably the model.

Other possible extensions include describing the problem as a search model in an inter-temporal environment. This should produce a negative sloped demand for loans at each bank and then, give some power to each lender to change its rates.

CHAPTER 2
ENDOGENOUS BORROWER PREFERENCES FOR BANKS AND BANK SWITCHING PROBLEMS IN A SEARCH MODEL OF LENDING

Introduction

In view of the current financial crisis caused in part by excessive lending and mis-categorization of borrowers, it is relevant to re-evaluate our modeling of the banking industry to analyze possible equilibrium prices that might put the long-term stability of the economy at high risk. Most of the current literature that analyzes credit rationing and government regulation assumes a banking market either as a monopoly or one in perfect competition. Papers such as Von Thadden (2001) and Hauswald and Marquez (2003) that analyze oligopolistic price competition result in mixed Nash equilibria that are inherently difficult to use as starting points in more complex theoretical models, in addition to the unsatisfactory implication that banks randomize their pricing decisions. This chapter analyzes how borrowers choose to approach lenders in a search model of lending. This is a step towards a characterization of the banking industry which yields clearer predictions.

Considering the fact that some lenders have the ability to serve better certain borrowers, the model analyzes the existence of banks with “high quality signals” and “low quality signals.” A bank with a high quality signal is one which is more accurate when categorizing borrowers. Detragiache et al. (2008) show that local banks seem to better focus services on small local firms, while international banks tend to focus on larger multinational firms. Their theoretical model considers two types of banks, foreign and domestic, in which one type is better than the other at monitoring certain kind of information (p.2124). The model in this chapter also considers a market in which one lender can be better at categorizing certain borrowers than the other lenders.

This chapter provides two major conclusions. First, the borrowers' preferred level of accuracy depends on the profitability of projects and the differences in projects' risk. When the profitability of safe projects is high and the differences in projects' risk is relatively low, all borrowers will prefer to apply first to lenders with low quality signals. These lenders will be providing loans at low interest rates for all, without much knowledge of their real risks. This is much like what happened before the financial crisis of 2008. Now that profitability of safe projects is low, the opposite occurs; all borrowers prefer to apply first to lenders with high quality signal since the other banks are lending at high interest rates to all.

A second important result is that when a borrower that has a relationship with a bank decides to switch banks, even for reasons other than the interest rate offered, the borrower will be perceived by the market as a "lemon," or one with higher probability of being risky. Although previous literature has shown empirically that bank loans are more easily available for new and small businesses than for firms who have had different lending relationships[1], there is little theoretical work that clearly shows why this is the case. In this sense, this chapter of the dissertation may help to fill some of that void.

In sum, this chapter analyzes both endogenous borrower preferences for banks and lender switching problems in the context of an optimal stopping problem, also a search model of lending.

The existing literature most closely related to this analysis is Vesala (2007) and Greenbaum et al. (1989). The latter paper is a search model of lending that focuses on bank-borrower relationships. The model has a lender with an informational advantage

[1] Paravasini (2008).

and a set of other lenders that face perfect competition. Greenbaum et al. do not analyze the case of borrowers of different risk levels applying for loans and focuses on the longevity of bank-borrower relationships. This paper also differs from the study in this chapter in that it has explicit search costs that drive in part the main results of the paper, and in the fact that a borrower is switching lenders carries no additional information about the type of borrower.

Vesala (2007) studies the effect of switching costs for a borrower on profits and interest rates of an incumbent lender who has an informational advantage. His main result is that the incumbent's profit as a function of switching costs is U-shaped and hence, there is "relation formation" when these costs are very low or very high. In Vesala's paper, switching costs are given and independent of the type of borrower. This is an important difference with the present analysis.

This chapter is organized as follows. Section two presents the characteristics of the model. Section three analyzes the equilibrium policies. Section four analyzes formation of endogenous borrower preferences for banks by interpreting the results previously stated and adding a bank with informational advantages. Section five considers the problems borrowers face when they want to switch lenders. Detailed proofs are in the appendix.

Model

This chapter develops a particular type of stochastic discrete choice model, an optimal stopping problem. There are some agents with the opportunity to invest in a safe project and others who can invest in a risky project. Both must search for a lender to fund the investment. Assume initially that all lenders are equal. A borrower will randomly order lenders and approach one by one until an acceptable interest rate is offered[2]. As soon as a lender is found, the project in undertaken and profits are realized. Initially, after profits are collected, the borrower exits the market. Later in the chapter it will be assumed the same borrower may come with a new project and have a recurring relationship with a bank by applying for a loan first at the same bank that funded the previous investment.

Consider the following notation:

Let S_i be the signal observed by a lender from borrower *i.* When time reference is necessary S_i^t will be used, where the superscript refers to the time period. The probability that any random borrower is of type *y* is $\mathrm{p_y}$. Given this probability we can define the following probabilities:

$Prob(S_i = X|i = Y) \equiv p_{xy}$ (This is assumed exogenous)

$Prob(i = Y|S_i = X) \equiv p_x^y = \frac{p_y p_{xy}}{\sum_i p_i p_{xi}}$ (This reflects the accuracy of a signal[3])

Since information will be accumulated through time, this chapter defines a history up to period *t*, h_t, as the sequence of previous observations starting with the latest one $(S_i^t, S_i^{t-1}, \dots, S_i^1)$. Applying this definition to the definition of accuracy, we have

$$Prob(i = Y|S_i^t = A, h_{t-1}) = p_{A\,h_{t-1}}^y$$

Finally, let *r* be the interest rate and *R* be total amount that a borrower must repay, or one plus the interest rate.

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[2] Given that simultaneous offers in oligopolistic competition creates mixed equilibria in prices, I assume that lenders are approached one at a time in order to make the search model more tractable. The existence of pure strategy equilibria in price policy functions, as described in Giraldo (2008), may be used in future research to allow for more intra-period competition.

[3] A high accuracy signal is one which has a high probability of identifying correctly a borrower's type. For example, if there is a signal s such that $p_s^y = 1$, the signal is perfectly accurate since any time s is observed, a lender knows for sure that the type of the borrower is *y*.

Players and Information

The economy modeled consists of borrowers, who have no capital available for investment, and lenders, who do not have direct access to projects but do have capital for investment. A borrower may have access to a set of risky projects or safe projects, and hence they will be called risky (r) and safe (s) respectively. A borrower's type does not change with time, so that a borrower is always safe or always risky. There are also many lenders that initially have access to the same information technology. Heterogeneity in lenders will be introduced later in the chapter.

A lender observes a history of signals, up to period t-1, plus its own observation, which is either L or H. L is an indication the borrower is risky. H indicates the borrower is safe. The signal structure is simple to make the model easier to analyze since a signal is observed in each of an infinite number of possible periods[4]. Let $p_H^s = p_L^r > 1/2$. In other words, there is a strict positive correlation between observing signal H and the borrower actually being safe, and between observing L and the borrower actually being risky. Assume the lenders' signal observations, conditional on type, are iid; for each borrower searching, the signal that may be observed by other banks in the future is not correlated with previous observations but only with the borrowers' own type, which does not change with time. Previous signal outcomes for the same borrower are publically observable, although similar results would hold if it is only assumed that some information about a borrower becomes public after each search, as long as the information set still grows with time. This assumption will be relaxed in the last section of the chapter. In conclusion, each lender's information is composed by two parts: all

[4] This is also standard in this type of literature. See Sharpe (1990), Vesala (2007), and many others.

the public information about a borrower, this part grows with time as more and more searches take place, and a new signal which is independent of the previous information, given the borrower's type.

Each project undertaken may succeed or fail. If a borrower succeeds, he earns revenues equal to $k + \theta_i$ and if he fails, he earns $k - \theta_i$. For a risky borrower θ_i=θ_2 and for a safe borrower θ_i=θ_1, where $\theta_2 > \theta_1$. Let g_1 be the probability a safe project succeeds and g_2 the probability a risky project succeeds. The cost to carrying out any project is one. Hence, the amount borrowed is one. Let k>1 and $\theta_i \in (k-1, k)$ for i=1,2 so that an unfavorable outcome will always make revenues less than the amount borrowed, but at least zero. Using this set up with different success probabilities and different dispersions I can analyze both first and second order stochastic dominance.

A riskier θ_2 project in the first order dominance sense implies that the profits given θ_1 are greater that those given θ_2, which implies $g_2\theta_2 < g_1\theta_1$[5]. In the second order dominance sense, for $g_2\theta_2 = g_1\theta_1$ (mean preserving spreads), we have $\theta_2 > \theta_1$. In any of the two cases we must have $g_2 < g_1$ in order for the designation risky/safe to be appropriate.

Sequence of Moves

For each borrower, these are the steps of his search. Step 5 will be slightly modified later in the chapter.

1. The borrower applies for a loan at any one lender
2. The lender obtains a signal for the applicant and makes an interest rate offer
3. The borrower accepts or rejects the offer

[5] $g_2(k+\theta_2) + (1-g_2)(k-\theta_2) - 1 < g_1(k+\theta_1) + (1-g_1)(k-\theta_1) - 1$, the expected profits of the risky investment are lower than those of the safe investment.

4. If the offer is accepted, then the investment is made and profits are collected in that same period.

   If the offer is rejected, no income is realized and the offer is withdrawn.

5. The next period comes. If previous offers were rejected, the borrower re-starts the process with a new lender. If a previous offer was accepted, the borrower exits the market.

After an investment is undertaken, if the same borrower has a new investment idea, it will initially come in the market as a new borrower about whom nothing is known. Although this may seem unrealistic, it simply narrows the analysis to one project per borrower. In the last section switching costs is analyzed and this assumption is relaxed by letting information about previous investment outcomes be available to the lender who made the loan.

Action Sets and Strategies

Borrowers are the agents searching and their decision consists of finding a rule that determines when to stop looking, accept the interest rate offered, and make the investment. Lenders on the other hand decide what interest rate to offer to each type of borrower.

Since a risky borrower is associated with a dispersion θ_2 and a safe one with θ_1, the lenders' profits given a borrower with dispersion θ_i accepts the offer are ρ(R|θ_i) = g_i*(R) + (1-g_i)(k-θ_i) - 1.

The borrower's profit function given its type is π(R|θ_i) = g_i*(k+θ_i-R)

The borrower's problem is to $\max_{\{\mathrm{d(t)}\}_\mathrm{t}} E\{\sum_{t=1}^{\infty} \delta^{t-1}\, \pi(R_t) d(t) | \Omega(t)\}$ where d(t) is equal to zero when the offer at period *t* is rejected, and d(t) is equal to one when the interest rate offered at period *t* is accepted. Let d(t)=0 for every period after an offer is accepted. $\Omega(t)$ is the information set at time t. δ is the discount factor.

The value function for a borrower of type *i* is

$$V_i(t) = \max\{d(t)\pi(R_t), \delta E[V_i(t+1)|\Omega(t)]\}.$$

Equilibrium Analysis

The solution to the search problem from the borrowers' perspective consists of a sequence of reservation values below which the offer is accepted, and above which it is rejected. So, if $R_i^t \leq \overline{R_t}$ then $d(t) = 1$; otherwise, d(t)=0. According to this behavior, lenders decide their offers.

Let's analyze first how each type would behave in a separate market where there is only one type of borrower. A stationary equilibrium yields a time independent reservation rate $\bar{R}$ so that V[Ω(t), $\bar{R}$] = E{V[Ω(t+1), $\bar{R}$]}. A stationary reservation rate is such that the borrower is indifferent between accepting today and waiting another period. Formally, π($\bar{R}$|θ) = δ $E[V(t+1)|\Omega(t), \bar{R}]$

Hence,

$$g(k + \theta - \bar{R}) = \delta g(k + \theta - \bar{R})$$

which means, $\bar{R} = k + \theta$.

Then, if both types were in separated markets, all projects would make zero profits.

Note that the reservation rate for the safe borrower, $\overline{R_s}$, is smaller than that of the risky borrower, $\overline{R_r}$. Consequently, there is no reason to ever make offers less than $\overline{R_s}$ since both borrowers will accept this amount (provided no other lender will offer a smaller rate either).

Now consider again both borrowers participating in the same market. For the risky borrower it is **not** possible to find a stationary reservation value since a positive probability of being miscategorized in the future as safe makes the reservation value dependent on the history at each time period. Recall that safe borrowers will consider accepting an offer up to k+θ_1. Then, a lender will offer at most k+θ_1 to those he believes to be safe. Any higher offer will only be accepted by the risky borrower. This means that any borrower will be offered k+θ_1 if the lender considers him to be safe. A risky borrower may consider a higher offer depending on the probability of getting k+θ_1 in the future. Let m_t be the probability that a borrower will get an offer of k+θ_1 in period t, which depends on $\Omega(t)$.

Proposition 1: In equilibrium, $\overline{\mathrm{R_r}} \geq \mathrm{k} + \theta_2 - \delta(\theta_2 - \theta_1)$ if $\mathrm{m_t}$>0 for any t; and , $\overline{\mathrm{R_r}} = \mathrm{k} + \theta_2$ for $\mathrm{m_t} = 0$. The proof is in the appendix.

Given this behavior by borrowers, a lender must decide its interest rate policy. The lenders' decision making depend on its expected profits from each possible interest rate offer. Given $\mathrm{h_t}$,

$$\rho(R) = \begin{cases} p_{h_t}^r[g_2(R) + (1 - g_2)(k - \theta_2)] + p_{h_t}^s[g_1(R) + (1 - g_1)(k - \theta_1)] - 1 \; if \; R \leq k + \theta_1 \\ p_{h_t}^r[g_2(R) + (1 - g_2)(k - \theta_2)] - 1 \; if \; R > k + \theta_1 \end{cases}$$

Proposition 2: Offers from banks will be either $k + \theta_1$ or $k + \theta_2$.

Proof is in the appendix.

$k + \theta_1$ will be offered at any t, instead of $k + \theta_2$, if

$$p_{h_t}^r g_2(k + \theta_1) + p_{h_t}^s S_1 \geq p_{h_t}^r g_2(k + \theta_2) \qquad \text{(2-1)}$$

where $S_1 = g_1(k + \theta_1) + (1 - g_1)(k - \theta_1) - 1$, the expected surplus of the safe project.

Written differently, if

$$y_t \equiv \frac{p_{h_t}^s}{p_{h_t}^r} \geq \frac{g_2(\theta_2 - \theta_1)}{S_1} \qquad \text{(2-2)}$$

an offer of $k + \theta_1$ is made. If (2-2) does not hold, the offer is $k + \theta_2$. Let this strategy be called OS for Optimal Strategy.

Note that since within a period each bank is not competing, banks will try to charge as loan payment the highest return of the expected borrower's type project.

Assumption 1: $p_{Lr} > p_{Hr}$ and $p_{Hs} > p_{Ls}$.

Corollary 1: Given a risky borrower, $\lim_{t\to\infty} E\left\{\frac{p^s_{h_{t+1}}}{p^r_{h_{t+1}}}\right\} = 0$ and hence, $\lim_{t\to\infty} m_t = 0$.

Corollary 1 states that as more information becomes available, the probability that a risky borrower is mis-categorized as safe goes to zero. As a consequence, the interest rate offers will tend to stay high as time increases.

Proposition 3: For all $\alpha < 100$, there exists an n_α such that after n_α observations, lenders can be α% sure of the type of borrower.

This is an application of the law of large numbers. For a detailed proof and the value of n_α see the Appendix.

For a safe borrower, y_t tends to infinity since $p^s_{h_t} \to 1$ and $p^r_{h_t} \to 0$ as t→∞. This implies that a safe borrower should keep applying for loans until a favorable offer is made since the law of large numbers guarantees there is a *n* such that the offer at *n* will be *k*+θ_1; and a risky borrower that has received all $k + \theta_2$ offers will accept this interest rate after certain number of periods searching since for a risky borrower y_t tends to zero.

In strategy OS, h_t is only relevant in what it says about the probability of being safe. Note that y_t may have the same value for different histories. For example, (L,H,L,H) and (L,H). Hence, the offer is the same since the information the histories convey is the same, although *t* is different.

At period t+1, a lender may observe an h_t with L **and** Hs. This is because a borrower may get H but get an offer of $k + \theta_2$, according to rule OS. This may occur when there are many Ls before a lender observes H or when the signals are not accurate. If this hypothetical borrower is safe, he should wait and apply for more periods until h_t is such that the offer is $k + \theta_1$.

If lenders act as established by strategy OS, risky borrowers will reject k+θ_2 if there is a positive probability that tomorrow the offer is k+θ_1 since expected profits would be positive. $k + \theta_1$ is offered with positive probability when there is a j such that with positive probability $S_{t+j} = H$ and if

$$y_{t+j} \equiv E\left\{\frac{p^s_{H,h_{t+j-1}}}{p^r_{H,h_{t+j-1}}}\right\} \geq \frac{g_2(\theta_2-\theta_1)}{S_1} \qquad \text{(2-3)}$$

This expression states that if I can expect a better offer in the future, I should reject the current one.

Equilibrium Cases:

Pooling Equilibria.

Case I: If at time *t* condition (2-2) holds for any history, all borrowers will get an offer of $k + \theta_1$.

(2-2) may hold for any history in the first stages of the game. For example, when the signal provides little information and an L signal in the first period still allows for a reasonable probability that the borrower is safe, formally when $\frac{p^s_L}{p^r_L} > \frac{g_2(\theta_2-\theta_1)}{S_1}$[6].

Inequality (2-2) is also more likely to hold for any history when the difference in the projects' risks is small, and the profitability of the safe project is high.

[6] The right hand side of the inequality must be less than one for this to be true. So, profitability of the safe project must be relatively high and risk differences, relatively high.

In this equilibrium all borrowers get the same offer in the first period, and all accept it. All investment opportunities are carried out during the first period. The risky borrower gets higher profits than the safe borrower, who gets zero profits. This type of equilibrium implies that all borrowers are investing in projects at low interest rates, the market has little information on the true risks, and risky projects are making positive profits whereas safe projects are making zero profits. If after the project has been funded, but before the loans are repaid, banks realize the difference in risks were higher than initially estimated; the probability of success for the risky and/or the profitability of safe projects is lower than anticipated, as occurred in the US in 2008, the expected value of the loans will decrease significantly. All borrowers with an L signal are now expected to generate losses[7]. The experiences of 2008 have taught us that this type of equilibrium represents a huge risk to an economy, particularly since most of these loans are traded in the derivatives market and the realization of miscalculated risk parameters plummeted their values. This case shows that perfectly rational agents might put the economy in risk just by maximizing their own individual profits and using the available information in the market.

Case II: All borrowers will get an offer of $k + \theta_2$, at time *t*, if (2-2) does not hold for any history and any current observation. This may be the case in the first stages of the game. For example, when $\frac{p_H^s}{p_H^r} < \frac{g_2(\theta_2 - \theta_1)}{S_1}$.

This is an equilibrium, much as in today's financial sector, where even a favorable signal does not increase the probability of being safe to a level such that banks are willing to lend at low interest rates. This occurs when there is a combination of low

[7] A higher offer should have been made and since economy would not be in this case I any longer.

accuracy in the signals and low profitability of safe investments. Note that safe borrowers will opt to search for more periods until there is enough information in the market that indicates they are safe. The action of risky borrowers depends on whether (2-3) holds. Since the signal is inaccurate and the right hand side of the inequality (2-3) is high, it is likely that (2-3) will not hold early in the search. Hence, risky borrowers may accept this high interest rate offer in early periods. In conclusion, risky projects end up being funded first. The safest investments will be carried out in later periods, which means that investment in the first periods is smaller in this case than in the previous case. Since all the projects being considered in this chapter have expected values greater than zero, they will all be financed eventually. However, in cases such as this pooling equilibrium investors must search for more periods and the benefits of investment opportunities are not observed in the initial periods.

Note that the common characteristic of both cases is that there may be pooling equilibria in the early stages of the game, particularly when the signal is not very accurate and the probability of a misleading observation is high. A signal that cannot be trusted leads to equilibria equivalent to those where there is no signal at all. However, since a bad signal still carries some information about the true type of a borrower, as more observations become available the true type of the borrower will be revealed, and as time increases the probability of observing banks pricing in a pooling equilibrium diminishes.

Separating Equilibria.

Case I: $\frac{p^s_{H,h_t}}{p^r_{H,h_t}} \geq \frac{g_2(\theta_2-\theta_1)}{S_1}$ and $\frac{p^s_{L,h_t}}{p^r_{L,h_t}} \leq \frac{g_2(\theta_2-\theta_1)}{S_1}$. This will always happen with signals of high quality (high correlation with the truth) and as time goes to infinity. Hence, with accurate signals and in later periods of a search high signals get a low interest rate offers and low signals get a high interest rate offers. This is the standard result we observe in most of the related literature.

Note that the higher the market information quality, the further $\frac{p_H^s}{p_H^r}$ is from one and the shorter the expected search time for all individuals. This happens because case I of the separating equilibria occurs sooner and the true type is revealed to the market faster. In other words, the safe borrowers are getting H in the earlier periods with higher probability and risky borrowers that get L in the initial periods will soon lose hope they will be able to deceive a lender. On the other hand, low market quality signals may look like credit crunches, or accentuate them, as search time increases for all borrowers.

A set of graphs that can be found in the appendix illustrate the equilibrium cases described above. The graphs consider the different cases that can occur for a given $\frac{g_2(\theta_2-\theta_1)}{S_1}$, and a given $\frac{p_{X,h_t}^s}{p_{X,h_t}^r}$, as $\frac{p_{Y,h_t}^s}{p_{Y,h_t}^r}$ changes, for X=H and Y=L; or vice versa.

In conclusion, the profit functions for a lender are:

Given a risky borrower=

$$\rho(risky) = \begin{cases} Early\ (taken\ as\ safe) = p_{h_t r}[g_2(k+\theta_1)+(1-g_2)(k-\theta_2)-1] \\ Later = g_2(k+\theta_2)+(1-g_2)(k-\theta_2)-1 \end{cases}$$

Given a safe borrower=

$$\rho(safe) = g_1(k+\theta_1)+(1-g_1)(k-\theta_1)-1$$

A table of results can be found in the Appendix. The table includes the expected profits for all agents and the fraction of loans assigned in each possible equilibrium case after the first searching period.

Different Signal Qualities

In this section I will explore what happens if there is a lender with better information technology than all the rest. Consider the following two cases.

Case I: $\frac{g_2(\theta_2 - \theta_1)}{S_1} > 1$. This inequality will be true when there is a high difference in risk among borrowers and the profit margin of the safe borrower is not very high. A high probability the risky project succeeds also increases the probability of being in this case.

Let there be a lender such that its probability of being correct and the borrower is indeed safe when an H is observed, is greater than that of other lenders, $p_H^* > p_H^s$. Call this the "accurate" lender and the rest, "inaccurate" lenders. Note that, $\frac{p_H^*}{1-p_H^*} > \frac{p_H^S}{p_H^r}$. By strategy OS, if all inaccurate lenders offer in the first period $R_1 = k + \theta_1$ then the offer of the accurate lender, R_1^*, will be $k + \theta_1$.

The strategy OS still applies in periods two and higher, only now probabilities will be updated according to a high accuracy of the first signal and lower accuracy for the following ones.

In this case 1, it is possible that the signal of the accurate lender satisfies (2-2) but the inaccurate signals do not, and p_H^S is still greater than p_H^r. If this were true, all inaccurate lenders will offer $k + \theta_2$ for all observations in the first period while the accurate lender is separating according to its signal. Hence, all borrowers weakly prefer to apply first to the best technology in the market, and those who obtain an L signal will approach the worst lenders afterwards. This case is similar to the results in the literature studying lending to informationally opaque firms where borrowers will tend to approach lenders who are better at evaluating their true risk and providing any specific services they need[8].

In this case, a low observation will always yield an offer of $k+\theta_2$ in the first period since $\frac{p_L^*}{1-p_L^*} < \frac{p_L^S}{p_L^r} < 1$, which means (2-2) does not hold.

If $\frac{g_2(\theta_2-\theta_1)}{S_1} = 1$, both lenders are always separating. Since all signals are informative $\frac{p_L^*}{1-p_L^*} < \frac{p_L^S}{p_L^r} < 1$ and $\frac{p_H^*}{1-p_H^*} > \frac{p_H^S}{p_H^r} > 1$, which means that by strategy OS both lenders always have the same policy, they are both always separating borrowers according to their independently observed signal.

Proposition 4: When the accurate lender is separating according to its signal, so that an observation of L gets a high interest rate offer and an H gets a low one, all borrowers will approach the accurate lender in the first period.

If the accurate lender is separating, safe borrowers will prefer the accurate lender since they will get an H observation and an offer of k+θ_1 with higher probability. But then the inaccurate lender knows that all its pool of first time applicants is risky, which implies all the offers will be high interest rates. Hence, the accurate lender will be at least weakly preferred. The formal proof can be found in the Appendix.

This proposition also implies that if one lender has privileged information regarding a particular borrower, due to previous lending relationships for example, this lender will be approached first by such borrower when it is separating. Note that when this lender is **not** separating, this is not necessarily the case, the borrower may prefer to break the relationship and look for a new lender with its new project. This case is analyzed next.

[8] Berger et al. (2001); Detragiache et al. (2008).

Case II: $\frac{g_2(\theta_2-\theta_1)}{S_1} < 1$. This occurs when there is a low difference in risk among borrowers and the return of the safe borrower is relatively high.

Using an analogous analysis, we may observe all inaccurate lenders offering $R_1 = k + \theta_1$ to all borrowers in the first period, independent of the observed signal. Namely, when $(1 >)\frac{p_L^S}{p_L^r} > \frac{g_2(\theta_2-\theta_1)}{S_1}$, but the opposite is true for the lender with the best signal and, as established by strategy OS, $R_1^* = k + \theta_2$ upon observing L. Hence, for any borrower with a positive probability of getting an L signal, he weakly prefers to approach first the lenders with the inaccurate signal since he is pooling with low interest rates for all. There is indifference if the accurate lender is separating, by proposition 3.

This is a risky situation for an economy in that most borrowers would be evaluated by the worse signal and more risky borrowers would acquire loans at low interest rates. This would make loans hard to value, particularly if it became known that the profitability was initially overvalued by all and differences in risks were under appreciated, such as two years ago. Both mistakes would make this equilibrium easier to occur.

Note that for a given θ_1, higher θ_2 will increase the chances of any borrower receiving an offer of $k + \theta_2$ and case 1 from above will be more common. In other words, when there is a high risk difference among borrowers, making a mistake in categorizing them is more costly, which will make lenders charge higher rates on average[9].

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[9] Regarding the investment in new technologies by banks, this model concludes that the effect of an increase in p_H^S (having observed high) in profits is positive since $E\{\rho|\theta_1\} > E\{\rho|\theta_2\}$ and by Proposition 3. Because the best technology in the market gets approached first *when all banks are separating*, the pool of loan applicants for banks approached in t≥2 is less favorable, as only those who got a signal of L are still searching. Then, all banks will invest until the increase in profits equals the increase in costs (standard Euler equation).

Switching Analysis

This model can also be used to analyze the problem of switching lenders. Previous literature suggests that borrowers that are looking for a first time for a lender can get better loan terms than those trying to switch lenders. This set up allows us to study why this may be the case. In this section let h_{t-1} be unobservable except for the fact that a history exists or it does not. In other words, the only thing observable is that a borrower has searched before or that he has never searched, hence borrowers can only be classified as those applying for a first time and those who have applied elsewhere at least once and have rejected the offers.

Assume from now on, just to simplify the number of cases to study, that $\frac{p_H^s}{p_H^r} \geq \frac{g_2(\theta_2-\theta_1)}{S_1}$ and $\frac{p_L^s}{p_L^r} \leq \frac{g_2(\theta_2-\theta_1)}{S_1}$, so there is always separating equilibrium.

If a borrower has a new project and he applies first to the lender that funded the last project, we say there is a lending relationship. This relationship provides useful inside information about the future success probability of an investor since a borrower does not change its type. In particular, even if the outcome of the project is not observable, past signals from the same borrower are observable. Assume a borrower-bank relationship may break for exogenous reasons (changes in customer service, a bank mistake that was too costly, etc[10].) in addition to very high interest rate offers. Since risky borrowers will receive high offers from banks that learn that they are indeed risky, these borrowers are expected to have a higher incentive to switch lenders. Let $h_t = w$ if the borrower is switching and $h_t = \emptyset$ if it is a new borrower in the market.

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[10] See Howorth et al. (2003).

Consider first a safe borrower. In order to decide whether to switch, this borrower calculates its expected offer from the next lender[11].

$$E(R_w|s) = p_{Hs}\left\{(k+\theta_1)*1\left(\frac{p^s_{H,w}}{p^r_{H,w}} \geq \frac{g_2(\theta_2-\theta_1)}{S_1}\right) + (k+\theta_2)*1\left(\frac{p^s_{H,w}}{p^r_{H,w}} < \frac{g_2(\theta_2-\theta_1)}{S_1}\right)\right\}$$
$$+ p_{Ls}\left\{(k+\theta_1)*1\left(\frac{p^s_{L,w}}{p^r_{L,w}} > \frac{g_2(\theta_2-\theta_1)}{S_1}\right) + (k+\theta_2)1\left(\frac{p^s_{L,w}}{p^r_{L,w}} \leq \frac{g_2(\theta_2-\theta_1)}{S_1}\right)\right\}$$

Since

$$\frac{p^s_{X,w}}{p^r_{X,w}} < \frac{p^s_X}{p^r_X} < \frac{p^s_{X,h_t}}{p^r_{X,h_t}} \text{ for } X\epsilon\{H,L\} \qquad (2\text{-}4)$$

Then, the expected offer for a safe borrower in the first period (one who is new in the market) is lower than that of a safe borrower who is switching, but higher than that of a safe borrower who stays in the lending relationship.

If there is a lender with a better signal $\frac{p^*_{H,w}}{1-p^*_{H,w}} > \frac{p^s_{H,w}}{p^r_{H,w}}$; since for the safe borrower p_{Hs} is high, $E(R_w|s) \geq E(R^*_w|s)$.

A safe borrower is more likely to switch to the bank with the best signal. The lower $p^s_{X,w}$ (the higher the information asymmetry created by the known private information withheld by the previous bank, compared to a borrower without such asymmetry; or the more difficult it is to convey information to new lenders about one's good standing in the financial market), the lower the chances of observing a switch, since the cost of doing so will be higher. This result is in line with those of Sharpe (1990) and in Greenbaum et al. (1989)[12].

Consider now a risky borrower.

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[11] Remember future lenders only know a borrower is switching. So, all lenders with whom there is no relationship are equal.

[12] See also Ongena and Smith (2001).

The expected offer for a risky borrower is

$$E(R_w|r) = p_{Hr}\left\{(k+\theta_1)*1\left(\frac{p^s_{H,w}}{p^r_{H,w}} \geq \frac{g_2(\theta_2-\theta_1)}{S_1}\right) + (k+\theta_2)*1\left(\frac{p^s_{H,w}}{p^r_{H,w}} < \frac{g_2(\theta_2-\theta_1)}{S_1}\right)\right\}$$

$$+ p_{Lr}\left\{(k+\theta_1)*1\left(\frac{p^s_{L,w}}{p^r_{L,w}} > \frac{g_2(\theta_2-\theta_1)}{S_1}\right) + (k+\theta_2)1\left(\frac{p^s_{L,w}}{p^r_{L,w}} \leq \frac{g_2(\theta_2-\theta_1)}{S_1}\right)\right\}$$

Since $\frac{p^s_{X,w}}{p^r_{X,w}} < \frac{p^s_X}{p^r_X}$ but $\frac{p^s_{X,h_t}}{p^r_{X,h_t}} < \frac{p^s_X}{p^r_X}$, risky borrowers starting their search have a lower expected offer than those switching, and lower expected offer than those staying in their lending relationships.

And, if there is a lender with a better signal such that $\frac{p^*_{L,w}}{1-p^*_{L,w}}$[13] $< \frac{p^s_{L,w}}{p^r_{L,w}}$; since for a risky borrower p_{Lr} is high, $E(R_w|r) \leq E(R^*_w|r)$.

A risky borrower is more likely to switch to the "worse" lenders. Again, the higher the negative effect of switching, the less likely borrowers are to switch since the probability of getting a high offer is greater.

Note that if a borrower has a relation with the same bank for n periods, and n is large enough so truth is known, then each borrower will get offers corresponding to the maximum they are willing to pay. Since the expected offer after switching lies in the interval $[k+\theta_1, k+\theta_2]$, the risky borrower is more likely to switch[14]. Hence, banks' belief that most borrowers switching are risky is reasonable.

As in Sharpe (1990), safe borrowers have higher switching costs since changing lenders implies breaking a relationship with someone who knows you are safe, whereas risky borrowers have little to lose from searching for a new lender, and more so as time

[13] $p^*_{L,w}$ being the probability that the borrower is safe given that he is switching and got a signal of L from the better lender.

[14] Recall $k+\theta_1$ is the maximum a safe borrower is willing to pay.

passes and its true type is revealed with almost certainty to one bank. This is also consistent with the literature that shows that less dependent borrowers hold longer bank relations[15]. Since risky firms tend to switch sooner, it follows that the average interest rate for firms that have long relationships is lower than those with shorter relationships, as is shown by Petersen and Rajan (1994), and Berger and Udell (1995).

Conclusions

This chapter develops an optimal stopping problem where borrowers are searching for a lender that can fund their project. Projects can be risky or safe. The model concludes that lenders may pool or separate borrowers in their interest rate offers depending on the differences in riskiness of the projects, the profitability of the safe projects and the lenders' monitoring technologies. The pooling equilibria are particularly interesting since they reflect conditions we observe in the financial markets during, before and after the crisis of 2008/2009. It is shown that it may be optimal to offer a low interest rate offer to every borrower or a high interest rate to all when the quality of the signal is bad. When there is no clear difference between a risky and a safe borrower, a market may end making numerous loans at low interest rates to borrowers from whom little is known, or interest rates may be high for all borrowers so that owners of safe projects are forced to hold investments until more information can be made publicly available.

In addition, borrowers may prefer to approach lenders with a high accuracy or a low accuracy depending on whether the inaccurate banks are pooling with a low interest rate for all, a high interest rate, or if they are separating borrowers. When banks with

[15] Ongena and Smith (2001).

low accuracy offer low interest rates to all borrowers, project owners will approach these banks first so that for most loans made little information is known about the borrower. A small difference in risk among projects and low average signal quality increase the risk of this happening.

The chapter finalizes with an analysis of the implications of the model regarding the problems faced by borrowers trying to switch banks. It is shown that risky lenders are more likely to switch banks since they have lower costs of switching.

CHAPTER 3
ALLOCATION OF RESEARCH RESOURCES: DYNAMICS OF ANALYSTS' COVERAGE

Introduction

Financial analysts are essential players in the financial markets. Their main role is to gather information about stocks and interpret it so that investors can make more informed trading decisions. Thus, they help improve efficiency through the dissemination of information regarding publicly traded firms. For this reason understanding their allocation of effort across different companies is very important for those interested in the capital markets.

The extent to which analysts can help the market depends on the costs of doing so and the demand for such information. I focus on the effects of the costs generated by the information environment, while controlling for several important demand variables. The main goal of this chapter is to evaluate to what extent information accuracy is important in determining allocation of research resources and, in particular, to quantify the effects of information problems. In order to do that this chapter focuses on the changes in the number of analysts studying and predicting performance of publicly traded stocks.

Every analyst that makes predictions and recommendations on the value of a stock is tracked by the IBES dataset. Most of these analysts work for consulting firms or for the research departments of brokerage firms. Profits are generated by selling the information or, as is documented by Juergens and Lindsey (2009), through increased trading (this is only valid for brokerage firms).

The empirical analysis is based on available information on analysts' coverage, information quality and firm specific data. I run a series of ordered probit regressions that evaluate the changes in coverage as a function of previous analysts' accuracy, revisions, and some firm specific and sector characteristics.

I find that coverage decreases on average with higher previous errors in estimation, and physically large firms have smaller decreases in coverage as a result of inaccurate information. The data also shows those stocks with higher previous market values have higher probabilities of observing decreases in coverage. Higher past revisions also decrease coverage.

This chapter of the dissertation evaluates empirically some of the hypothesis in Bhushan (1989) and emphasizes the relationship between number of analysts studying a firm, firm characteristics, and the information environment of a firm. Some of his results include that large firms have more informative prices, and hence announcements have a lesser impact on trading, and that the marginal cost of collecting information decreases with firm size.

Ackert and Hunter (1994) study analysts' behavior. They highlight that analysts' forecasts tend to outperform time-series forecasting models. The authors describe analysts as showing a "dynamic form of rationality" and show there is herding behavior among analysts as a consequence of risk avoidance, even when this implies acting against private information. Analysts also seem to be consistently overly optimistic. Trueman (1992) explains however that the more accurate the analyst, the smaller the incentives he has to herd. Ackert and Hunter also study the salary of analysts as a function of their ability.

The model in this chapter is similar to Weitzman (1973) and Tandon (1983) in terms of the problem it tries to answer.   Weitzman is concerned about the allocation of resources under free access and private ownership, while Tandon studies the allocation of resources particularly to research. The literature on allocation of resources to research is quite extensive, with the two mentioned papers being only examples; the study of empirical evidence and the application of these findings to the financial sector have, however, not being fully explored. The empirical papers on the topic belong mostly to the accounting literature, and hence evaluate the significance of certain accounting measures in explaining stock coverage. Examples include Loh and Stulz (2009); Barron et al. (1998) and Hayes (1998). Of these papers, the closest to this chapter is Barron et al. The authors study how the properties of analysts' forecasts reveal information about the informational environment. This analysis, using appropriate lags to avoid endogeneity, looks at the inverse problem, which stocks do analysts research as a function of its informational environment.

The rest of the chapter is organized as follows. The following section includes some background information with general facts about the market and incentives problems that may shape analysts' behavior. A third section explains the model. Section four explains the empirical results. Finally, after some robustness checks, the last section includes the main conclusions of the chapter.

Industry Background

The importance of financial analysts for the capital markets has been recognized for long. Much of the trading activity that occurs is based on the recommendations from analysts and on the general expectations of their reports. For this reason the government has increased its regulation of this market since dishonest reports and activities on the part of analysts were discovered at the end of the 1990's.

Understanding the environment in which analysts operate since the new regulations took effect is essential in the study of their coverage decisions.

Analysts tended to “make excessive ‘buy’ recommendations and inflated earnings forecasts.”[1] The reasons to do so varied from an increased ability to get privileged information to the salary incentives and other conflicts of interest[2] . Hence, since the early 2000’s the industry has been increasingly regulated.

Communication with firms is regulated by the SEC’s regulation fair disclosure, also known as regulation FD. This regulation exists since 2000 and forbids disclosure of select information to any investor(s). All announcements and releases must be public.

Analysts are also forbidden from sharing information about their reports before they are published or from misreporting information for personal gain. It was the violations of these rules by several investing firms during the late 1990’s and early 2000’s that gave rise to the Global Settlement of 2002. This is an agreement achieved in 2002 between US government regulators and 12 large (at the time) investing companies that prevents analysts from sharing information with brokers within an investment firm by requiring both departments (research and brokerage) to be separated both physically and with the so-called Chinese walls. Budget allocation to both departments must also be independent.

In 2002, another set of rules constrained analysts’ compensations (they cannot be tied to the performance of investment banking or the brokerage business) and analysts’ personal trading activity. Nowadays analysts must present a series of exams that test

[1] Hovakimian and Saenyasiri (2009). Page 1.

[2] See Hovakimian and Saenyasiri (2009) for detailed information on the incentives problems.

them on their economic and finance knowledge as well as their understanding of the regulations. They must also maintain their registration through a submission of documents that should show there are no conflicts of interest in their activities.

According to Hovakimian and Saenyasiri (2009), both the Global Settlement and regulation FD reduced biases for all analysts (whether with the firms that signed the agreement or with any other). However, analysts may still have a tendency to be optimistic according to the literate on the topic. For example, Easterwood and Nutt (1999) show that analysts overreact to good news and underreact to bad news. The herding behavior discussed in the introduction is another reason why systematic errors in the predictions may still exist (the mean error of the predictions is not necessarily zero).

Research Design

Sample and Data

The data was collected from the IBES and Compustat datasets. IBES is a comprehensive data set on earnings forecasts that contains data on who is studying which firms; what are their predictions; what were the actual values of a set of predictable variables such as revenues, share values, etc.; among other data. Compustat contains firm specific data. In all models the predictions used for the estimations were those for earnings per share for the next fiscal year. My observations start in 2006 for the IBES data and 2005 for the Compustat data (one more year to generate a variable growth of sales and then lag it) and end in 2008. This period seemed appropriate since there were accounting measure changes in 2005 in the datasets, and before then the decision making of analysts on which firms to cover and how to make predictions was greatly influenced by illegal practices and subsequent changes in regulations, as I explained in the background section. The total number of observations include 420 different estimators(firms that hire analysts); 5,858 different analysts; 5,974 different firms being analyzed and 18,022 different actual values (targets) being forecasted in different occasions by different analysts.

Not all 18,022 could be matched with the Compustat dataset; some were dropped because the trading firm was sold during a year and there was conflicting data those years, in addition to structural differences that may be present in the model during these transition periods; "targets" with one analyst reporting only one estimate were also dropped[3]. The time series information is used to generate the explanatory variables but the estimation only uses the transformed data for 2008.

After estimating all necessary variables and eliminating the mentioned observations, the final data set has 2743 stocks, 43% of which trade in NYSE, 52% trades in Nasdaq, and the rest trade in other smaller exchange markets.

Variable Description

Analysts= Total number of analysts in the market who made forecasts about the earnings per share for a particular stock in 2008.

Change analysts= One-year change in the total number of analysts covering a particular stock.

Estimators= Number of estimators (a firm that employs analysts) who made forecasts about the earnings per share for a particular stock in 2008.

Change estimators= One-year change in the number or estimators covering a firm.

[3] Estimating the variable "revisions" makes little sense when there is only one prediction.

lserr= Absolute value of the average error of the analysts' forecasts for the previous year. This was scaled (divided) by earnings per share to make the errors comparable across firms. The lag is used in the regressions to avoid endogeneity problems.

This variable is expected to indicate the certainty with which the earning per share in a particular firm can be estimated, i.e. the accuracy of the available information. According to Barron et al (1998), an increase in mean errors may occur together with an increase in uncertainty and/or in analysts' consensus.

lsrev= Average of the analysts' revisions of the forecast for a firm's earnings per share for the previous fiscal year. Revision per analyst is estimated as maximum estimation minus smallest estimation. This variable is also scaled (divided) by earnings per share and the lag is used in the estimations also to avoid endogeneity problems. Lsrev is expected to indicate how much the information that can be learned of the firm changes during one year.

Employees= Number of employees in the firm. The variable is in thousands. The hypothesis is that large firms are easier to study because they have more economic significance and hence there is more public interest in them and more publically available information. Bhushan (1989) found evidence that the cost of finding information about firms changes with their size.

Growth= One year percent change of sales. The lag of this variable is used in the estimation. There are potentially conflicting effects of this variable on coverage, which makes the sign difficult to predict. On one hand, an increase in sales indicates a growing firm with great potential for profits, an increasing interest on it, and hence great potential for gains from collecting information about it. On the other hand, firms that are growing fast are also firms going many internal transformations. In fact, the accounting literature has found a relationship between internal control problems and sales growth (Wang, 2009). Hence, these are also firms with higher levels of uncertainty and less reliable announcements.

Lagmktval= Lag of the firm's market value. The variable is in Millions. Higher Market value is expected also to raise interest in the stock and hence to create a higher demand of information. This hypothesis will turn out to be incorrect, as will be shown and discussed in the results.

Lagactual= Lag of the reported earnings per share (eps). This variable measures potential benefits from understanding a stock but will prove to be insignificant.

Grearnings= Growth of total earnings. The lag of this variable was tried in the estimations.

Sector dummies= dummy per GIC sector. There are 10 sector classifications.

Exchange market dummies= Dummy per market in which the stock trades. The stock market variable is separated in the following 6 groups: NYSE, NYSE alternext US, Nasdaq_nms stock market, NYSE Arca, Other-OTC.

The interpretations of the variables "lserr" and "lsrev" are in accordance with the recommendation of Barron et al. (1998).

Table D-1 shows the summary statistics of the variables that appear in the final regressions and that proved to be empirically relevant.

Preliminary Tests

To further understand the data, the appendix includes three frequency graphs. Figure C-1 shows that most changes in coverage are small, with a small bias towards positive changes. In addition, most stocks are covered by one analyst (Figure C-2) and most estimators are relatively small (less than 10 analysts working in it –Figure C-3-). This means that possible profits are not highly concentrated, i.e. there are enough niches for multiple small firms to succeed.

Since it is likely that higher coverage of a stock results in more accurate estimations a test was performed to be certain of the interpretation of the error variable. The full sample was separated in those stocks with average coverage over the last three years above the median, and those below it. The median is 6.2 analysts. Although the mean error for the subsample with large coverage is smaller than the mean error of stocks with small coverage, the difference is statistically insignificant.

Research Model

The model is estimated as an ordered probit, using only observations from 2008. In order to guarantee all the possible outcomes had enough observations to estimate the probabilities, I regrouped the tails of the distribution so that every group had at least 18 observations in it. For changes in analysts greater than 9 or smaller than -8 the observations were grouped and called 10' and -10', respectively. For changes in estimators, the firms with absolute changes greater than 7 were grouped together, and the groups were labeled 10' and -10'. Hence, the label 10' in the tables in the appendix refer to large changes of around 10 analysts (or estimators). The final distributions are in appendix D (Tables D-2 and D-3).

Different regressions are run to evaluate the effect of past errors and past revisions on stock coverage. Both variables are not in the same regression to avoid the high correlation between them to bias the coefficients. The ordered probit was estimated with changes in coverage as the dependent variable. This would control for time invariant variables (at least short-time invariant) that may affect the level of coverage, such as, management structure or economic and political situations with effects not explained by growth, size and market value.

All regressions were run with two separate versions of the dependent variables: the number of analysts and of estimators. Because of potential problems with the levels' estimations, those results are not reported here, although they are available upon request. The results reported in the appendix do not include "actual" nor "growth of earnings" although those variables were tested and the results are also available. The effect of growth of earnings on coverage seems to be through the same channel as that of market value since when they are included in the regression together their coefficients become insignificant, with no major changes in the rest of the coefficients. "Actual" is simply insignificant in the estimations of changes of coverage. Since the reason for including these variables was similar to the reason for including market value, the results reported here include only market value. This also allowed the order probit to be run with a larger sample.

Other tests that were performed on the model are explained in the "Robustness Tests" section.

Empirical Results

Number of Analysts

The coefficients for the ordered probit that evaluate the changes in coverage, with errors as an independent variable, can be found in Table E-1. All the coefficients are significant at the 10% level, except for growth in sales. It is possible that both effects described in the "variable description" section are in effect and perfectly cancel each other, so that the internal control problems and unreliability of the information coming from a firm with high growth is offset by the potential gains from learning about such firms.

The results for the marginal effects of the changes of analysts' coverage are in Table E-2. The table shows that the probability that the number of analysts stays the same with an increase in the absolute value of the average error decreases; the same happens to the probability that the number increases by one, although the fall is larger. On the other hand, the probability that coverage decreases by one goes up. These results indicate that previous errors represent a real cost in gathering information and cause a decrease on the number of analysts. For example, all else equal, an *increase* of one standard deviation in the lagged scaled error causes an increase of 0.003 in the probability of a *reduction* in coverage by one analyst; this is an increase of 1.8%.

Errors in estimations are relevant determinants of both large and small changes in coverage, and the changes caused by the realization of the inaccuracy may be significant. For example, an *increase* of one standard deviation in the lagged scaled error causes an increase of .04 in the probability of a *reduction* of around 10 analysts in coverage. This is 10% of the estimated probability of observing such a decrease. A decrease in past errors causes an almost equal increase in the probability of observing around 10 more analysts covering a stock.

Similar estimations were performed for a more aggregated coverage variable. Changes in coverage were separated into three groups: positive, negative or no change. In this case all coefficients became insignificant. This happens because most changes in the data are small, and hence they occur within each of the three groups, in addition to the natural increase in standard errors and hence the tendency to find more insignificant coefficients when the data is grouped. In other words, grouping the dependent variable too much may cause a serious loss of information.

The differences between the reported marginal effects and those estimated with lagged earnings per share as an additional variable are extremely low, some being identical; when growth in earnings was included the differences were greater although still similar in magnitude to the ones reported here.

High lagged market value is significant in explaining why some firms have increases/ decreases in coverage. However the result obtained here is opposite to what was expected, and opposite to Hayes' (1998) conclusion that "analysts' incentives to gather information are strongest for stocks that are expected to perform well" (p.299), although in this dissertation the relationship of higher coverage was expected as a consequence of good performance in the past. The marginal effects in Table E-2 show that stocks that represent firms with higher market value have a slightly higher probability of observing a *decrease* in coverage. Possible explanations can be that these are firms with higher levels of coverage and then changes are more likely to be negative (marginal profits from an increase in coverage are very small when the starting point is already high), or that firms with higher market value are less likely to continue increasing in value. According to the estimations, a one standard deviation increase of lag market value increases the probability of a reduction in coverage of around 10 analysts by close to 0.00056, which is a 14.6% increase.

Table E-2 also indicates that physically large firms, those with more employees, tend to have a higher probability of increases in coverage. These firms may be harder to ignore and small changes can attract analysts to find out potential gains from physically large firms. Large firms are also less likely to have their coverage reduced, indicating again that when firms have potential to bring large benefits from information, there is a commitment to learn about the firm and coverage is not reduced easily. This is also consistent with Bhushan's (1989) result that the marginal cost of collecting information decreases with firm size, so that it is less costly to maintain more coverage in large firms. For example, an increase of one standard deviation in the number of employees increases the probability of an increase in coverage by 5 analysts by 0.001, which is an 8% increase[4].

The other possible independent variable to explain the information environment is revisions, which refers to the amount that can be learned, or the volatility of information, during the "research period" of a stock. Firms with high revisions are also firms that require more continuous investigation.

The results show there is a real cost to uncertainty. Table E-3 shows the coefficients of the ordered probit with their respective significance. The results are extremely similar to those of Table E-1. Table E-4 shows that all firms that had higher revisions in previous periods, have a lower probability of not observing changes in coverage and of observing increases in coverage. Said differently, higher revisions in previous periods cause a significant decrease in coverage. For instance, a one standard deviation *increase* in the lag of revisions causes a *decrease* in the probability of observing one more analyst covering a firm by 0.003, which is 1.9% of the estimated probability. Note that past scaled revisions are significant at the 1% level across all reported categories of the dependent variable.

[4] Firms that trade in the New York Stock Exchange tend to have larger coverage, followed by Nasdaq, all else equal.

The results for revisions are consistent under different specifications and the effects of the other variables are the same as when lag of scaled errors is used. In fact, for some estimations the marginal effects are identical.

Number of Estimators

Estimators don't withdraw from the market or increase in numbers depending on previous errors or revisions –Tables E-5 and E-6.- They may change the number of analysts assigned to a stock, but there seems to be a commitment to provide a prediction from a stock once the estimator has engaged in learning about it. In fact, all variables lose their explanatory value. It is possible that estimators withdraw from researching a stock due to political/ economic expectations, long-term trends, going/coming into business, etc.

Robustness Checks

Testing Other Variables

Leuz (2003) highlights the importance of institutional characteristics such as risk as complementary factors affecting the number of analysts. Although this study is concerned about changes, the volatility of trade volume was introduced into the model. This variable was insignificant in all the regression in which it was tested. For this reason it is not included in the final results.

A second test was to evaluate if the effect of errors depends on the value of the stock. It is possible that errors in estimating earnings of a valuable firm would generate different reaction than if the mistake was made with a stock with lesser value. In order to study this possibility a dummy variable was created which equaled one for observations that had a lagged market value in 2008 above the median. This variable was interacted with error. This variable was also insignificant in all regressions in which it was tested[5].

Spliting the Data

In order to further test the reaction to errors in estimations for different observations, the sample was divided according to the number of employees in the firm the stock represents. The median of this variable is 1.533. Those firms that had a mean size, or number of employees, below the median were labeled as being small and the rest were labeled as being large. The model was run for both types separately.

Large firms have a smaller average error and significantly larger market value, as can be seen in tables D-4 and D-5. Growth of sales is higher, on average, for large firms.

The main conclusion is that lagged scaled error is insignificant for the smaller firms, whereas it is highly significant for the large firms. A possible explanation for this is that stocks with of large firms are expected to present smaller errors since the cost of gathering information for large firms is smaller, and hence there is a large reaction to observed errors in the past. On the other hand, larger errors in predictions are expected from smaller firms, so that there is at most a small reaction to observed mistakes.

The same occurs with revisions; large revisions are only relevant for large firms.

Tables E-7 and E-8 show the results for the large firms. The distribution of changes in this sample is in Table D-6. The marginal effects are now smaller than for the full sample, but the difference is statistically insignificant. A one standard deviation

[5]Different ways to split the sample according to market value were tested, all with the same results. Both the volatility variable and the interaction term were added to the ordered probit on their own, and then together. They were always insignificant. The inclusion of volatility reduced the sample size by around 700 observations.

increase in the errors cause a 1.2% increase in the probability of observing a reduction in coverage by one analyst, and a decrease of 5.6% in the probability of observing a 5 analyst increase in coverage.

Tables E-9 and E-10 show the same regressions but using lag of revisions. The results are again very similar as those for the regressions with the “errors” variable. A one standard deviation increase in the revisions made about stocks representing large firms causes a 1.8% decrease in the probability of observing an increase in coverage by one analyst.

Table E-11 shows the coefficients for the order probit for small firms. The distribution of changes in this sample can be seen in table D-7. The results show that lagged scaled errors are not significant in explaining changes in coverage. Table E-12 shows the marginal effects. Since both subsamples present very few changes of coverage of more than 10 analysts, the marginal effects were not considered reliable, and hence are not reported. Although the sample could be regrouped to estimate more marginal effects, the purpose of this section is to compare results with the rest of the chapter, and hence regrouping would still not allow us to compare the causes of large changes in coverage for small or large firms versus the entire sample.

For the “small firms” sample the results indicate that although lagged errors become insignificant, lag of market value is more important than for the whole sample. For example, the reduction in the probability of observing less coverage (five analysts less) when the market value increases is almost two times higher for this subsample than for the large firms.

Tables E-13 and E-14 show the regressions using lag of revisions for small firms. The results are again very similar to those with “errors” as a variable.

Conclusions

The series of ordered probit regressions run in this chapter shed some light on the dynamics between information quality and allocation of resources to information extraction. In sum, higher previous errors represent a real cost in the collection of information and hence cause a reduction in coverage. The same is true for revisions, they represent a real cost of uncertainty.

Firms with high market value have a higher probability of observing a decrease in their coverage than firms with lower values, while those with more employees require lower costs to be analyzed and hence have higher coverage.

When the data is split in large and small firms, past errors are only significant for the first group. This could happen because lower costs from studying a large firm makes expected errors very small.

CHAPTER 4
GENERAL CONCLUSION

The first model in this dissertation looked at a lending model where borrowers made a onetime decision: they apply to all banks at once and borrow from that one which offered the lowest interest rate. The second model has borrowers who apply to one bank at a time, and they keep searching until an acceptable interest rate offer is made. Because in the first model there is no opportunity to learn through time about the quality of a borrower, time periods are identical in terms of information quality. In this scenario efficiency is more easily achieved when there is a specialized market, in other words, each firm has a high ability to recognize borrowers' risk for one particular type of borrower. More symmetric markets will not assign loans at the appropriate rate since risky borrowers may get the lowest interest rate offers.

The search model scenario allows for learning to occur in the market. Efficiency now is determined by macroeconomic factors such as profitability of the safest investments and differences in riskiness among borrowers. This occurs because these factors determine which banks offer the lowest interest rate and hence, which banks make the loans. Compared to the previous model, efficiency does not depend on the differences in ability to analyze information on the part of the banks but on the borrowers' risk characteristics. Hence, the relevant agent to determine the distribution of resources in the banking sector changes according to the way we assume borrowers search for loans.

The empirical section of the last chapter, among other findings, shows there is in practice a reaction to information quality, validating the relevance of this area of research. The estimations show a real cost to uncertainty and a real change in allocation of resources according to the information environment. The changes captured in the model show that current information environment induce real changes in the distribution of resources that are economically significant.

APPENDIX A
PROOFS FOR CHAPTER 1

Proposition 1: Equilibrium when (1-2) holds.

The observed prices are indicated with an asterisk (*).

(i) By assumption, borrowers choose the lowest interest rate offered.

(ii) Competitor:

If $r_i^*(H) < r_j^0(H)$, then offering $r_i^*(H)$ gives negative profits to "j" for any S_j. Since any borrower for whom S_i=H will accept "i's" offer, all who accept any $r_j(H)$ higher than $r_i^*(H)$ will have S_i=L. Then, $r_j^*(H) = r_j^*(L) = r_i^0(L)$.

*If $r_i^*(H) = r_j^0(H)$, then $r_j^*(H) = r_i^0(L)$. In order to prove this, note the equivalence of the following two expressions for expected profits given φ_I observes high (both carry the same information): $p_{jH} * r_H - (1 - p_{jH}) = 0$ (Expected profits of j) and

$$k[(1 - p_{iL}) * r_H - p_{iL}] + (1 - k)[p_{iH} * r_H - (1 - p_{iH})] = 0 \qquad \text{(A-1)}$$

where *k* is the probability that the better estimation is low when φ_I observes high[1]. Also note that the first term is negative ($r_H < r_L$, which makes the first term in brackets equal to zero) while the second one is positive ($r_H > \frac{1-p_{iH}}{p_{iH}}$).

Assume v_j is high. If v_i is high, then this individuals will randomly choose a lender. If v_i is low, then these individuals will choose φ_I. Expected profits will now be

$$k[(1 - p_{iL}) * r_H - p_{iL}] + \frac{(1 - k)}{2}[p_{iH} * r_H - (1 - p_{iH})]$$

By (A-1), this is negative.

[1] $p_{jH} = (1 - k)p_{iH} + k(1 - p_{iL})$

If $r_i^*(H) > r_j^0(H)$ and (1-2) holds, then $r_j(H) = r_j^0(H) + \frac{\delta_1}{2}$ where $\delta_1 = r_i^*(H) - r_j^0(H)$. This interest rate gives positive profits to the competitor; hence, it is credible that if given the opportunity, it would undercut the lender with the informational advantage. Any $r_j(H) \in \left(r_j^0(H), r_i^*(H)\right)$ would work here. This pricing will be called undercutting from now on. Note that this is only valid if (1-2) holds. If it did not, the threat is irrelevant to "i" since the expected profit of charging a high interest rate to those for whom S_i=H but S_j=L is larger than that of getting the offer accepted at $r_j^0(H)$ for all whom S_i=H.

If $r_i^*(L) \le r_i^0(L)$ and $r_i^*(H) \in \left(r_j^0(H), r_j^0(L)\right)$ then "j" can undercut $r_i^*(H)$ as explained above and $r_j^*(L) = r_i^0(L)$ since only those with S_i=L will accept its offer if S_j=L with any offer that has at least zero expected profits. If $r_i^*(H) > r_j^0(L)$ then $r_j^*(L) = r_i^*(H) - \frac{\delta}{2}$ and all those who S_i=H and S_j=H will accept an offer from "j". Given (1-2), this behavior from the best lender is not an equilibrium.

If $r_i^*(L) \le r_i^0(L)$ and $r_i^*(H) = r_j^0(L)$, since $\left(1 - p_{jL}\right) * r_j^0(L) - p_{jL} = 0$, then

$$k[(1 - p_{iL}) * r_i^*(H) - p_{iL}] + (1 - k)[p_{iH} * r_i^*(H) - (1 - p_{iH})] = 0 \text{ and}$$

$$k[(1 - p_{iL}) * r_i^*(H) - p_{iL}] + \frac{(1 - k)}{2}[p_{iH} * r_i^*(H) - (1 - p_{iH})] < 0$$

where $k = \Pr(S_i = L | S_j = L)$

As a consequence $r_j(L) = r_i^0(L)$ and at most half of those for whom S_i=L could accept its offer (when $r_i^*(L) = r_i^0(L)$). Any lower interest rate gives negative expected profits.

*If $r_i^*(H) \le r_j^0(H)$ and $r_i^*(L) \le r_i^0(L)$ then $r_j^*(L) = r_i^0(L)$ because only those for whom S_i=L accept any offer for which expected profits are not negative.

If $r_i^*(H) > r_i^0(L)$ and $r_i^*(L) \leq r_i^0(L)$ this behavior is rather unexpected. “j” could offer a unique interest rate that undercuts $r_i^*(H)$ and get its offer accepted by those for whom S_i=H. If “i” only offers the interest rate $r_i^0(L)$, “j” can offer one rate slightly under this one and make positive profits. This would not be an equilibrium since “i”, by (1-2) holding, is not maximizing profits if it took into account the undercutting by the competitor as a response to its policy.

If $r_i^*(L) > r_i^0(L)$ then, again, undercutting is profitable given that S_j=L.

Lender with an informational advantage:

Given (ii), the only pricing policy that does not introduce “cheating” in the a third period and that maximizes profits, provided (1-2) holds, is $r_i^*(H) = r_j^0(H)$: any larger rate will be undercut, and any lower has lower profits; and $r_i^*(L) = r_i^0(L)$, for the same reasons.

No lender has an incentive to change its policy in the following periods.

Proposition 2: This is the equilibrium when (1-2) does not hold. By assumption, borrowers choose the lowest offered received.

(i) Competitor:

Let r^* be such that $\frac{r^*-r_i^0(H)}{r_j^0(L)-r_i^0(H)} = \Pr(S_j = L|S_i = H)$. Then, $r^* \in (r_j^0(H), r_j^0(L)]$ by (1-2) not holding.

If $r_i^*(H) \leq r^*$, $r_j(H) = r_j^0(H) + \frac{\delta_1}{2}$ where $\delta_1 = r_i^*(H) - r_j^0(H)$. By assumption of (1-2) not holding this behavior of “i” would be changed in the following period, then it is not an equilibrium move for “i.”

*If $r_i^*(H) > r^*$, then $r_j(H) = r^*$. Any higher offer will make "i" change its policy in the following period by undercutting ("cheating"); any lower offer lowers profits. This is by definition of r^*.

-If $r_i^*(L) \leq r_i^0(L)$ and $r_i^*(H) \geq r_i^*(L)$, then $r_j(H)$ will be determined as above. $r_j(L) = max\{r_j^0(L), r_i^*(L)\}$, this way the competitor can get its offer accepted by all (or half if the second is an equality) for whom S_i=H and half for whom S_j=L; or $r_j(L) = max\{r_j^0(L), r_i^*(H) - \varepsilon\}$, when he gets the offer accepted by all those for whom S_i=H. It depends of which bears more profits. In either case the first player will change its original strategy since it now has negative expected profits; since this case brings about cheating, it is not to be expected.

If $r_i^*(L) \leq r_i^0(L)$ and $r_i^*(H) < r_i^*(L)$, when $r_i^*(H) > r_j^0(L)$, then $r_j(L) = r_i^*(H) - \frac{\delta}{2}$; when $r_i^*(H) \leq r_j^0(L)$, then $r_j(L) = r_i^0(L)$. To see why

*Consider first the case $r_i^*(H) = r_j^0(L)$, since $\left(1 - p_{jL}\right) * r_j^0(L) - p_{jL} = 0$, then

$k[(1 - p_{iL}) * r_i^*(H) - p_{iL}] + (1 - k)[p_{iH} * r_i^*(H) - (1 - p_{iH})] = 0$ and (1-3) holds.

Then $r_j(L) = r_i^0(L)$ and at most half of those for whom S_i=L could accept its offer (when $r_i^*(L) = r_i^0(L)$). Any lower interest rate gives negative expected profits. The case of undercutting is trivial.

If $r_i^*(L) > r_i^0(L)$ then, again, undercutting is profitable given that S_j=L.

(ii) The lender with the informational advantage

Given (ii), the only pricing policy that does not introduce "cheating" in the following period and that maximizes profits, provided (1-2) does not hold, is $r_i^*(H) = r_j^0(L)$, since "i" prefers to get the most out of the few for which S_i=H but S_j=L, than to compete for all who get S_i=H, however, a higher interest rate introduces a profitable undercutting rate for the competitor given that he observes low in the third period such that "i" has no offer accepted; and $r_i^*(L) = r_i^0(L)$, since any higher will never be accepted and any lower gives negative profits.

No lender has an incentive to change its policy in the following periods.

The case of no asymmetry, or $p_{ih} = p_{jh}$ and $p_{il} = p_{jl}$, is explained in the text.

Deriving A and B: Let Pr(S_i=*h*) = A and Pr(S_j=*h*) = B. Normalize population size to one. The following table summarizes the proportion of borrowers that each lender can expect will be "good" or "bad" given the probabilities to observe a high signal and the accuracy of the signal. For each lender there are two instances when a borrower is good: when he observes a high signal and the signal is correct, or when he observes a low signal and the signal is wrong. By the same token, there two instances when a borrower is bad. This explains why there are four probabilities, or proportions, for each lender.

Table A-1. Probabilities

Lender *j*	Lender *i*
(1-B) p_{jl} borrowers are "bad"	A*p_{iH} borrowers are "good"
(1-B)(1-p_{jl}) borrowers are "good"	A(1-p_{iH}) borrowers are "bad"
B p_{jH} borrowers are "good"	(1-A) p_{il} borrowers are "bad"
B (1-p_{jH}) borrowers are "bad"	(1-A)(1-p_{il}) borrowers are "good"

Number of good borrowers: (1-A)(1-p_{il}) + Ap_{iH} = B p_{jH} + (1-B)(1-p_{jl})=θ
Number of bad borrowers: (1-A) p_{il} + A(1-p_{iH}) = B (1-p_{jH}) + (1-B) p_{jl}=1-θ
The two equations in chapter 1 follow from here.

APPENDIX B
PROOFS AND TABLES FOR CHAPTER 2

Proposition 1: In equilibrium, $\overline{\mathrm{R_r}} \geq \mathrm{k} + \theta_2 - \delta(\theta_2 - \theta_1)$ if $\mathrm{m_t}$>0 for any t; and , $\overline{\mathrm{R_r}} = \mathrm{k} + \theta_2$ for $\mathrm{m_t} = 0$.

Proof: Since $\mathrm{k} + \theta_1$is the smallest offer that any borrower will get, a risky borrower is willing to accept a higher offer today that is greater than or equal to an interest rate $\bar{\mathrm{R}}$ that makes him indifferent between accepting today or waiting for tomorrow's best possible offer. In other words,

$$\boldsymbol{g_2}(K + \theta_2 - \bar{R}) = \delta g_2(K + \theta_2 - K - \theta_1)$$

$$\text{Or, } \bar{R} = k + \theta_2 - \delta(\theta_2 - \theta_1).$$

If $m_t = 0$, then lenders have learned enough information so that it is clear the borrower is risky. Given that this information is public and that risky borrower are willing to pay up to $\mathrm{K} + \theta_2$, this will be the offer they receive, and accept, each period.

Proposition 2: Offers from banks will be either $\mathrm{k} + \theta_1$ or $\mathrm{k} + \theta_2$.

Proof:

1. Safe borrowers will accept offers up to $k + \theta_1$*.* Because both borrowers are willing to accept $k + \theta_1$*,* a lender that is maximizing profits has no reason to offer any lower rate upon observing any history or any signal.

2. Only risky borrowers will accept offers higher than $k + \theta_1$. If all banks $k + \theta_2$ to all borrowers they believe are risky, then it is optimal to also offer $k + \theta_2$ whenever observations indicate the borrower is risky. If banks offered an interest rate for risky borrowers strictly between $\bar{\mathrm{R}}$ (no lower value would be optimal from proposition 1) and $\mathrm{k} + \theta_2$, then any one bank would be able to increase its offer today, and still be accepted because the borrower would discount the expected profits of waiting one more

period. In addition, the minimum reservation value is strictly higher than $\bar{R}$ from proposition 1, so that the minimum optimal offer is now greater than $\bar{R}$. Every bank then has incentives to increase its offer for risky borrowers. No bank can change its offer at $K+\theta_2$ because this is the highest offer risky individuals would accept.

In other words, because there is no inter-period competition, every bank has incentives to charge the highest interest rate a borrower is willing to pay, given the information about the borrower's type collected via the signals.

Corollary : Given a risky borrower, $lim_{t\to\infty} E\left\{\frac{p^s_{h_{t+1}}}{p^r_{h_{t+1}}}\right\} = 0$ and hence, $lim_{t\to\infty} m_t =$ 0.

Proof: Let H take the value of 1 and L take the value 0. By law of large numbers $lim_{t\to\infty} \sum_{l=1}^{t} \frac{S_r^l}{t} = p_{Hr}$; so that as t→∞ , $\mathrm{h_t}$ is such that $\mathrm{p_{h_t,r}} \to 1$ and $\mathrm{p_{h_t,s}} \to 0$. Using Bayes rule, $p^s_{h_t} = \frac{p_s p_{h_t s}}{p_s p_{h_t s} + p_r p_{h_t r}}$ goes to zero as t goes to infinity. Since $p^s_{h_t} = 1 - p^r_{h_t}$, $lim_{t\to\infty} E\left\{\frac{p^s_{h_{t+1}}}{p^r_{h_{t+1}}}\right\} = 0$.

As t→∞ and $\frac{p^s_{h_{t+1}}}{p^r_{h_{t+1}}} \to 0$, there is a t^* after which (2-2) does not hold anymore. Hence, by strategy OS, $R_t = k + \theta_2$ and then, $m_t = 0\ \forall t \geq t^*$. QED.

Proposition 3: $\forall\alpha < 100, \exists \mathrm{n}_\alpha$ such that after n_α observations, lenders can be α% sure of the type of borrower.

Proof: Let H take the value of 1 and L take the value 0. Let $X_n = \sum_{t=1}^{n} S_i^t$. $\mathrm{X_n}$ is distributed binomial with mean np_{Hv} and variance $np_{Hv}(1-p_{Hv})$ for $\mathrm{v = r}$ if the borrower is risky (call this distribution R) and $v = s$ if he is safe (call this distribution S).

These distributions can be approximated to normal distributions for a large n. Lets use the text book conservative rule that the minimum number of observations, n_c, should be such that $min\{n_c p_{Hv}, n_c(1-p_{Hv})\} \geq 5$ for $v = r$ and s.

For n≥ n_c, define $\bar{X}_n = \frac{X_n}{n}$. The Lindberg-Levy Central Limit Theorem implies that each lender can be $(1-\alpha) * 100\%$ sure that any particular borrower's X_n~R, if $\bar{X}_n \in p_{Hr} \pm z_\alpha \frac{\sqrt{p_{Hr}(1-p_{Hr})}}{\sqrt{n}}$ and X_n ~S, when $\bar{X}_n \in p_{Hs} \pm z_\alpha \frac{\sqrt{p_{Hs}(1-p_{Hs})}}{\sqrt{n}}$. Since these two intervals may intercept, accurate estimations of the borrowers type cannot be made until both intervals are disjoint, which occurs when

$$p_{Hs} - p_{Hr} \geq \frac{z_\alpha}{\sqrt{n}}[\sqrt{p_{Hr}(1-p_{Hr})} + \sqrt{p_{Hs}(1-p_{Hs})}].$$

Let $n^* = [\frac{z_\alpha}{p_{Hs} - p_{Hr}}[\sqrt{p_{Hr}(1-p_{Hr})} + \sqrt{p_{Hs}(1-p_{Hs})}]]^2$. Hence, $n_\alpha = max\{n^*, n_c\}$.

Proposition 4: When the accurate lender is separating according to its signal, so that an observation of L gets a high interest rate offer and an H gets a low one, all borrowers will approach the accurate lender in the first period. (In case I: $\frac{g_2(\theta_2 - \theta_1)}{S_1} \geq 1$).

Proof: Given that the accurate lender is separating according to its signal, safe borrowers will decide to approach this lender first since the expected interest rate offer from the accurate lender is less than the one from the other lenders:

$$p_H^*(k+\theta_1) + (1-p_H^*)(k+\theta_2) < p_{Hs}(k+\theta_1) + (1-p_{Hs})(k+\theta_2)$$ [1]

Since this is known by the inaccurate lenders, they know all first time applicants are risky, which means they will charge them $k + \theta_2$. Since borrowers in this model must

[1] The right hand side is the expected offer given the inaccurate lender is separating. This lender(s) may also be pooling, but given the case they would only be pooling at $k + \theta_2$ for all borrowers, which is an even higher offer. The left hand side is the expected offer from the accurate lender.

choose only one lender to apply for a loan, it is clear the expected offer is lower if they apply to the accurate lender.

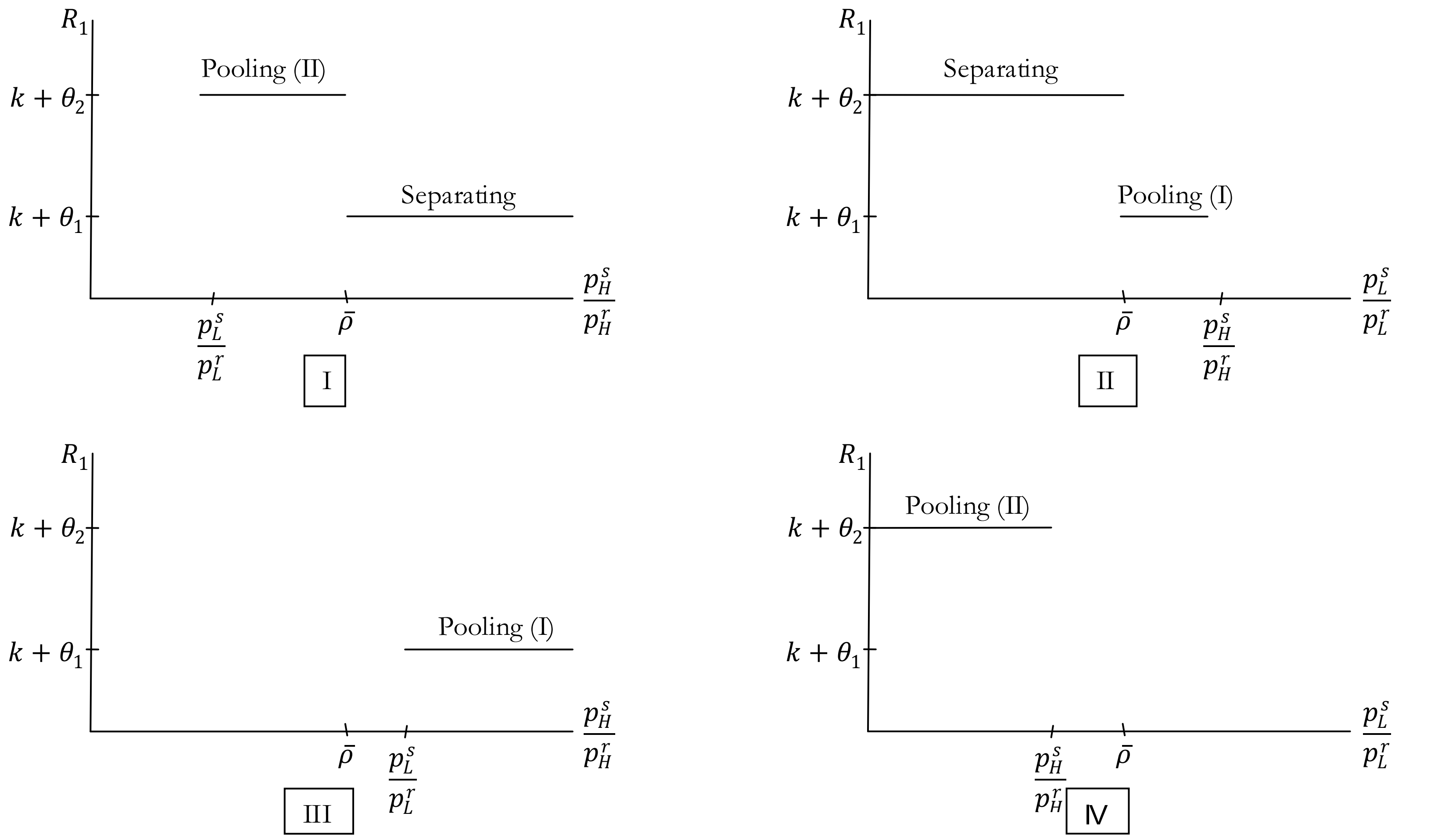

Figure B-1. Graphs of possible equilibrium cases

$\bar{\rho} = \frac{g_2(\theta_2 - \theta_1)}{S_1}$. All graphs correspond to the possible cases that can occur during the first period of a borrowers' search process. The interest rate graphed corresponds to the offer received by the lender with an H observation in the graphs I and III, and by the lender with an L observation in the graphs II and IV.

Table B-1. Table of results

Variables to be analyzed after the first period	Pooling $R_1 = k + \theta_1$ $\forall$borrowers	Pooling $R_1 = k + \theta_2$ $\forall$borrowers	Separating Equilibrium
Fraction of safe borrowers that get loans	100	0	p_{Hs}
Fraction of risky borrowers that get loans	100	0, p_{Hr}, or 1 *	p_{Hr} or 1 **
Fraction of total borrowers that get loans	100	p_r[0, p_{Hr}, or 1] *	$p_s p_{Hs}$ + p_r(p_{Hr} or 1)**
Bank's profits from a safe borrower	S_1	0	$p_{Hs} S_1$
Bank's profits from a risky borrower	$g_2(k+\theta_1) + (1-g_2)(k-\theta_2) - 1$	S_2***	$p_{Hr}[g_2(k+\theta_1) + (1-g_2)(k-\theta_2) - 1] + p_{Lr} S_2$
Safe borrower's profits	0	0	0
Risky borrower's profits	$g_2(\theta_2 - \theta_1)$	0	$p_{Hr}\, g_2(\theta_2 - \theta_1)$

The table assumes there are no liquidity constraints.

Recall equation (2-3) states that $\exists j: E\left\{\frac{p^s_{H,h_{t+j-1}}}{p^r_{H,h_t+j-1}}\right\} \geq \frac{g_2(\theta_2-\theta_1)}{S_1}$.

* If (2-3) holds for all borrowers, then 0; if (2-3) holds only for those for whom $S_i{}^t = H$, then p_{Hr} ; if (2-3) does not hold for any borrower, then 1.
** If for those who got a L signal, (2-3) holds, then p_{Hr} ; if it does not, then 1.
*** $S_2 = g_2(k+\theta_2) + (1-g_2)(k-\theta_2) - 1$

APPENDIX C
FIGURES FOR CHAPTER 3

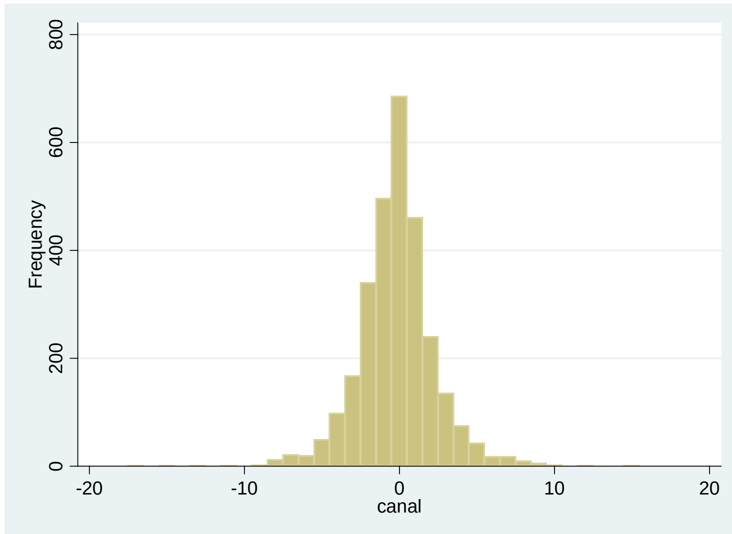

Figure C-1. Frequency: Change in number of analysts covering a firm

Canal= change in number of analysts covering a firm, from 2007 to 2008.

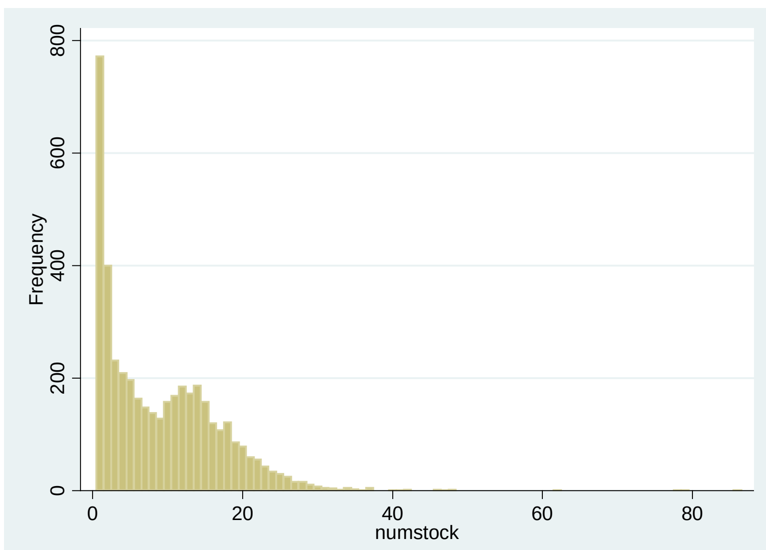

Figure C-2. Frequency: Number of stocks analyzed by one analyst

numstock= number of stocks analyzed by one analyst in 2008

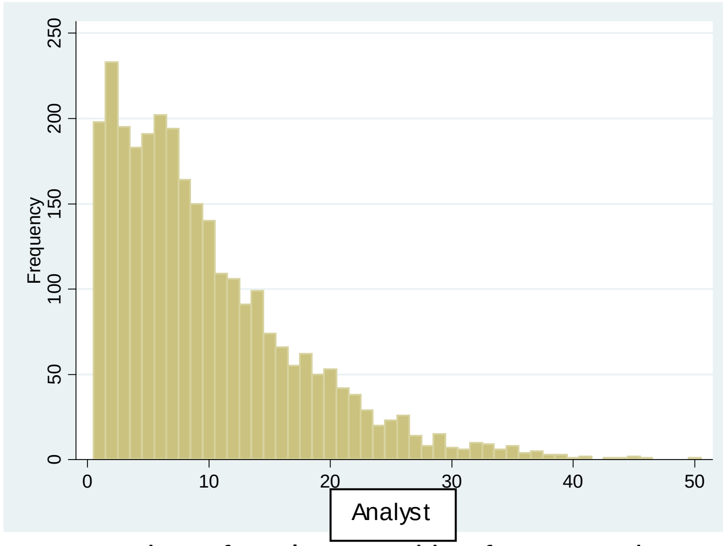

Figure C-3. Frequency: Number of analysts working for one estimator

Analysts= number of analysts working for one estimator in 2008.

APPENDIX D
SUMMARY STATISTICS FOR CHAPTER 3

Table D-1. Summary statistics for complete sample

Variable	Mean	Std. Dev.	Min	Max
Lag scaled error	.58580	4.20526	0	167.3231
Lag scaled rev	.76653	4.65598	0	213.7846
Lag mkt value	4937.405	19923.63	3.1547	504239.6
Employees	12.58478	50.07033	0	2100
Lag growth	1.09633	44.66729	-4.33098	2541.754

Table D-2. Frequencies: Change in the number of analysts

Change in number of Analysts	Frequency	Percentage
-10'	21	0.56
-6	44	1.18
-5	57	1.53
-4	115	3.09
-3	197	5.29
-2	431	11.57
-1	614	16.48
0	873	23.43
1	594	15.94
2	334	8.96
3	186	4.99
4	107	2.87
5	54	1.45
6	37	0.99
7	44	1.18
10'	18	0.48
Total	3726	100

Table D-3. Frequencies: Change in the number of estimators

Change in number of Estimators	Frequency	Percentage
-10'	18	0.49
-5 or -6	38	1.03
-4	76	2.06
-3	176	4.76
-2	333	9.01
-1	644	9.01
0	1017	27.52
1	620	16.77
2	360	9.74
3	177	4.79
4	107	2.9
5	60	1.62
6	40	1.08
10'	30	0.81
Total	3696	

Table D-4. Summary statistics for small-firms sample

Variable	Mean	Std. Dev.	Min	Max
Lag scaled error	0.67316	4.28725	0	164.63
Lag scaled rev	0.73469	2.17045	0	44.6875
Lag mkt value	639.9524	1212.926	3.1547	17019.51
Employees	0.46230	0.40739	0	1.531
Lag growth	0.50453	4.28317	-4.33098	94.52174

Table D-5. Summary statistics for large- firms sample

Variable	Mean	Std. Dev.	Min	Max
Lag scaled error	0.49488	4.16410	0	167.3231
Lag scaled rev	0.78352	6.11703	0	213.7846
Lag mkt value	9375.417	27801.76	18.0182	504239.6
Employees	24.70725	68.71069	1.535	2100
Lag growth	1.63221	61.249520	-0.86414	2541.754

Table D-6. Frequencies: Change in the number of analysts for large firms

Change of Analysts (Large Firms)	Frequency	Percent
-10’	13	0.70
-6	30	1.62
-5	31	1.67
-4	71	3.84
-3	120	6.48
-2	233	12.59
-1	291	15.72
0	359	19.39
1	285	15.40
2	171	9.24
3	110	5.94
4	63	3.40
5	30	1.62
6	16	0.86
7	22	1.19
10’	6	0.32
Total	1851	100

Table D-7. Frequencies: Change in the number of analysts for small firms

Change of Analysts (Small Firms)	Frequency	Percent
-10'	8	0.45
-6	13	0.72
-5	26	1.45
-4	43	2.40
-3	76	4.24
-2	183	10.20
-1	309	17.22
0	490	27.31
1	298	16.61
2	158	8.81
3	73	4.07
4	42	2.34
5	23	1.28
6	20	1.11
7	20	1.11
10'	12	0.67
Total	1794	100

APPENDIX E
TABLES OF RESULTS FOR CHAPTER 3

Results – Key:
* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

Table E-1. Coefficients: Lagged error on changes in number of analysts

Change in number of Analysts	Wald chi2 (17)=165.13 Pseudo R2= 0.0142	Prob > chi2 = 0.0000 Obs= 2741
	Coefficient	
lag scaled error	-0.00907**	
lag growth	-0.0026	
Employees	0.00076**	
lag mkt value	-2.33e-6*	
sector and exchange market dummies	Included	

Table E-2. Marginal effects: Lagged error on changes in number of analysts

	-10'	-5	-1	0	1	5	10'
Prob	0.00384	0.01473	0 .17885	0.24084	0.16213	0.01286	0.00261
Lag scaled error	0.0001**	0.00027**	0.00075**	-0.00019**	-0.00093**	-0.00023**	-0.00007**
Lag growth	0.00003	0.00008	0.00074	-0.00005	-0.00027	-0.00006	-0.00002
Employees	-8.71e-6**	-0.00002**	-0.00006**	0.00002**	0.00008**	0.00002**	6.15e-6*
Lag mkt value	2.67e-8*	6.96e-8*	1.93e-7*	-4.84e-8	-2.40e-7*	-5.98e-8*	-1.88e-8
Sector and exchange market dummies included							

Table E-3. Coefficients: Lagged revisions on changes in number of analysts

Change in number of Analysts	Wald chi2 (17)=166.71 Pseudo R2= 0.0140	Prob > chi2 = 0.0000 Obs= 2743
	Coefficient	
lag scaled revisions	-0.00672***	
lag growth	-0.00262	
Employees	0.00076**	
lag mkt value	-2.34e-6*	
sector and exchange market dummies	Included	

Table E-4. Marginal effects: Lagged revision on changes in number of analysts

	-10'	-5	-1	0	1	5	10'
Prob	0.00385	0.01473	0.17868	0.24067	0.16231	0.01285	0.00297
Lag scaled rev.	0.00008**	0.0002***	0.00056***	-0.00014**	-0.00069***	-0.00017***	-0.00006*
lag growth	0.00003	0.00008	0.00022	-0.00005	-0.00027	-0.00007	-0.00002
Employees	-8.75e-6**	-0.00002**	-0.00006**	0.00002**	0.00008**	0.00002**	6.93e-6*
lag mkt value	2.67e-8*	6.97e-8*	1.93e-7*	-4.79e-8	-2.41e-7**	-5.98e-8*	-2.12e-8
Sector and exchange market dummies included							

Table E-5. Coefficients: Lagged of scaled revisions on changes in number of estimators

Change in number of Estimators	Wald chi2 (17)=157.19 Pseudo R2= 0.0126	Prob > chi2 = 0.0000 Obs= 2740
	Coefficient	
lag scaled revisions	-0.00224	
lag growth	-0.00327	
Employees	0.00043	
lag mkt value	-1.63e-6	
sector and exchange market dummies		

Table E-6. Coefficients: Lagged error on changes in number of estimators

Change in number of Estimators	Wald chi2 (17)=156.79 Pseudo R2= 0.0126	Prob > chi2 = 0.0000 Obs= 2739
	Coefficient	
lag scaled error	-0.00208	
lag growth	-0.00326	
Employees	0.00043	
lag mkt value	-1.63e-6	
sector and exchange market dummies		

Table E-7. Coefficients: Lagged error on changes in number of analysts for large firms

Change in number of Analysts (large firms)	Wald chi2 (15)=132.23 Pseudo R2= 0.0191	Prob > chi2 = 0.0000 Obs= 1470
	Coefficient	
lag scaled error	-0.00692***	
lag growth	0.17566	
Employees	0.00071**	
lag mkt value	-2.55e-6**	
sector and exchange market dummies		

Table E-8. Marginal effects: Lagged error on changes in number of analysts for large firms

	-5	-1	0	1	5
Prob	0.01381	0.16454	0.20732	0.16555	0.01467
Lag scaled error	0.00019***	0.00048***	-0.00008*	-0.00064***	-0.0002**
lag growth	-0.00477	-0.01227	0.00211	0.01619	0.00514
Employees	-0.00002**	-0.00005**	8.51e-6	0.00007**	0.00002**
lag mkt value	6.93e-8*	1.78e-7**	-3.07e-8	-2.35e-7**	-7.47e-8*
Sector and exchange market dummies included					

Table E-9. Coefficients: Lagged revisions on changes in number of analysts for large firms

Change in number of Analysts (large firms)	Wald chi2 (15)=136.02 Pseudo R2= 0.0192	Prob > chi2 = 0.0000 Obs= 1471
	Coefficient	
lag scaled revisions	-0.0054***	
lag growth	0.17492	
Employees	0.00071**	
lag mkt value	-2.55e-6**	
sector and exchange market dummies		

Table E-10. Marginal effects: Lagged revisions on changes in number of analysts for large firms

	-5	-1	0	1	5
Prob	0.0.01379	0.16446	0.20727	0.16617	0.01466
Lag scaled rev.	0.00015***	0.00037***	-0.00006*	-0.00049***	-0.00016***
lag growth	-0.00475	-0.01224	0.00207	0.01618	0.00511
Employees	-0.00002**	-0.00005**	8.39e-6	0.00007**	0.00002**
lag mkt value	6.92e-8*	1.78e-7**	-3.02e-8	-2.36e-7**	-7.46e-8*
Sector and exchange market dummies included					

Table E-11. Coefficients: Lagged error on changes in number of analysts for small firms

Change in number of Analysts (small firms)	Wald chi2 (17)=75.15 Pseudo R2= 0.0163	Prob > chi2 = 0.0000 Obs= 1271
	Coefficient	
lag scaled error	-0.01531	
lag growth	-0.00477	
Employees	0.00237	
lag mkt value	0.00013***	
sector and exchange market dummies		

Table E-12. Marginal effects: Lagged error on changes in number of analysts for small firms

	-5	-1	0	1	5
Prob	0.0.01536	0.19572	0.28311	0.16122	0.00993
Lag scaled error	0.0005	0.00154	-0.0005	-0.00183	-0.00031
lag growth	0.00016	0.00048	-0.00016	-0.00057	-0.0001
Employees	-0.00008	-0.00024	0.00008	0.00028	0.00005
lag mkt value	-4.17e-6***	-0.00001***	4.18e-6***	0.00002***	2.58e-6**
Sector and exchange market dummies included					

Table E-13. Coefficients: Lagged revisions on changes in number of analysts for small firms

Change in number of Analysts (small firms)	Wald chi2 (17)=73.42 Pseudo R2= 0.0159	Prob > chi2 = 0.0000 Obs= 1272
	Coefficient	
lag scaled revision	-0.01236	
lag growth	-0.00479	
Employees	0.00432	
lag mkt value	0.00013***	
sector and exchange market dummies		

Table E-14. Marginal effects: Lagged revisions on changes in number of analysts for small firms

	-5	-1	0	1	5
Prob	0.0.0154	0.19542	0.28276	0.16111	0.00996
Lag scaled rev.	0.00041	0.00124	-0.0004	-0.00147	-0.00025
lag growth	0.00016	0.00048	-0.00016	-0.00057	-0.0001
Employees	-0.00014	-0.00043	0.00014	0.00051	0.00009
lag mkt value	-4.13e-6***	-0.00001***	4.09e-6***	0.00001***	2.54e-6**
Sector and exchange market dummies included					

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BIOGRAPHICAL SKETCH

Marcela Giraldo was born in 1982 in Pereira, Colombia. After the age of 4 she moved with her family to Bogota where she finished her high school education and started college. Between 2000 and 2001 Marcela lived in Washington State where she graduated from University Place High School. Upon her return to Colombia she enrolled in the Universidad de Los Andes in Bogota and she studied 5 semesters of Economics there.

In 2004 Marcela moved to St. Louis to finish her undergraduate studies at the University of Missouri-St. Louis. Then, she was admitted into University of Texas - Austin for a graduate program in Economics. After one year of successes, she decided to move to the University of Florida for new challenges. She plans to graduate on August of 2010 with a Doctorate in Economics.

Marcela married Brian Buckles in 2010. When this sketch was written Marcela had accepted a visiting professor position at Baylor University.