Essays in Financial Economics

by

Guodong Chen

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Doctoral Committee:

Associate Professor Sugato Bhattacharyya, Co-Chair
Associate Professor Christopher House, Co-Chair
Professor Stefan Nagel
Professor Amiyatosh Purnanandam

For my wife, Yu, and my son, Aaron

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TABLE OF CONTENTS

LIST OF FIGURES

Figure

LIST OF TABLES

Table

ABSTRACT

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Co-Chairs: Sugato Bhattacharyya and Christopher House

My dissertation consists of three chapters in different research areas in financial economics.

The first chapter studies the impact of house price expectations together with securitization, on the magnitude of risky mortgage lending by banks. As is well known, a nationwide drop in housing prices, followed by subprime mortgage defaults and downgrades of mortgage-backed securities, precipitated the U.S. financial crisis of 2007-09. This chapter first presents a simple model to explore the impact of both house price expectations and the growth of securitization on the extent of subprime lending. The model shows that a high expectation of housing prices not only increases lenders' willingness to lend to riskier borrowers, but, in addition, enhances the attractiveness of the originate-to-distribute (OTD) model of lending. Access to securitization markets also amplifies banks' incentives to lend to sub-prime borrowers and leads to a worsening of mortgage-market credit quality. Thus, when housing prices decline, the extent of defaults is magnified with OTD lending. Empirical findings confirm the model's predictions. In particular, the results show that, in markets with higher housing price growth, banks with higher OTD participation extended mortgages to riskier borrowers, and thus, had larger incidence of defaults once house prices declined.

The second chapter models the interaction between lending institutions and credit rating

agencies under different economic scenarios, where an originator window dresses claims it issues and a credit rating agency (CRA) screens. Both window dressing and screening efforts are shown to depend on the state of the economy: better states exhibit greater window dressing and less screening. The rating quality and default probability for given ratings also vary with economic conditions, and credit spreads adjust to such variations. When information sharing is allowed, the originator has asymmetric incentives to disclose information to the CRA.

The third chapter examines how retirement affects households portfolio choice. Conventional wisdom suggests that when income is substantially reduced after retirement, households should hold more safe assets in their portfolios. The data, however, show that, on average, retirement causes an approximately five to seven percent increase in the share of risky assets in households' portfolios. In addition, this positive shift mostly happens right after retirement immediately and is mainly driven by the fact that households without risky assets start to hold risky assets after retirement. Four factors that may be at play behind this large retirement effect are examined. Evidence in support of (a) shifts in risk tolerance and (b) spending additional time tracking the stock market is presented.

CHAPTER I

Housing Price Expectations and Subprime Lending: The Incremental Role of Securitization

1.1 Introduction

The financial crisis of 2007-09 began with subprime mortgage defaults and subsequent downgrades of mortgage-backed securities. In the aftermath, financial institutions have been blamed for having extended loans to borrowers of questionable creditworthiness, especially through subprime mortgages. Explaining financial institutions' lending decisions during this period is, therefore, of great importance to better understand the recent financial crisis.

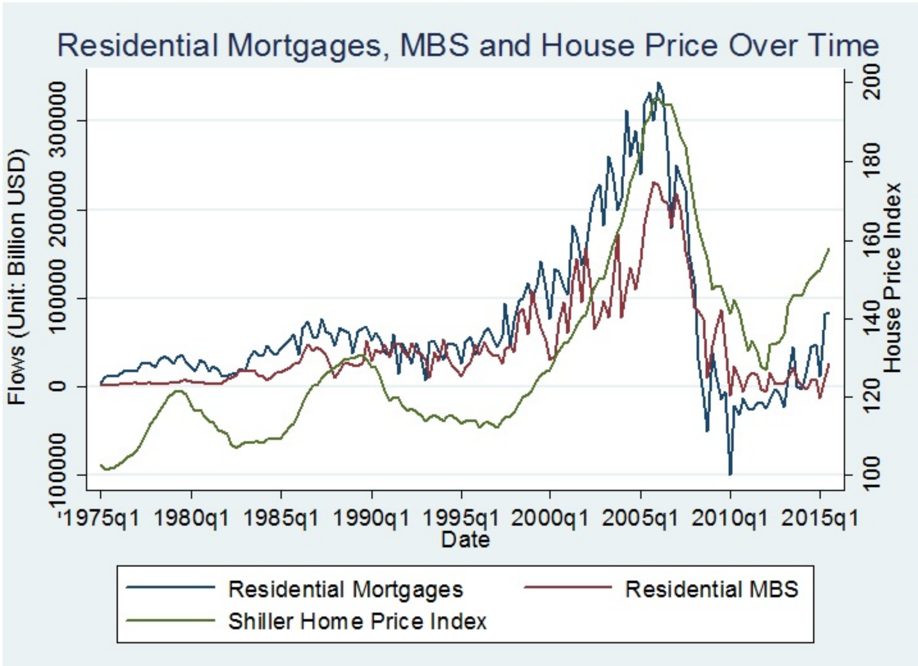
From the early 2000s up to 2007, high housing price growth and the boom in the securitization markets were two prominent, co-existing phenomena (Keys et al., 2012a). Both are, arguably, reasons that banks may have engaged in risky lending behavior.[1] On the one hand, high housing prices, by enhancing collateral values, increased banks' willingness to lend to borrowers of questionable creditworthiness.[2] Consequently, more borrowers with lower creditworthiness were able to obtain mortgages and home ownership hit its peak of 69 percent in 2004 (Keys et al., 2012a).[3] On the other hand, private label securitization and

[1]The patterns can be observed in Figures 1.1 and 1.2.

[2]See Foote et al. (2008), Foote et al. (2012), and Brueckner et al. (2012).

[3]At the same time, banks could recover the losses from defaulted mortgages more easily. As Keys et al. (2012a) point out, during the housing boom, the average time for banks to sell loans substantially shortened, from 16 months in 2000 to five months in 2006.

Figure 1.1: Mortgage, Mortgage-backed Securities, and Housing Price in U.S. Markets



Data source: 1) Federal Reserve Statistical Release and 2) Robert Shiller Home Price Index

the originate-to-distribute (OTD) model, popular during the same period, may also have contributed to having relaxed banks' lending standards due to agency misalignment (Purnanandam, 2011; Keys et al., 2012a). Several studies confirm this argument by documenting a resultant deterioration of average mortgage quality prior to the subprime mortgage crisis in 2007.[4]

To better reconcile all these patterns, following Brueckner (2000) and Brueckner et al. (2012), I build a simple model with borrowers' optimal default behavior to explore the impact of both house price expectations and the growth of securitization on the extent of banks' risky lending. In this model, borrowers apply for a mortgage equal to the current housing price P_0 and later make default decisions by comparing the prevailing housing price with the mortgage payment. Borrowers are heterogeneous in their default costs, which is a measure of a borrower's quality in this model. Based upon a borrower's quality, a bank decides whether to offer her a loan and at what rate. The bank has two options: either hold the loan on

[4]See Ashcraft and Schuermann (2008), Loutskina and Strahan (2009), Rajan et al. (2010), Loutskina (2011), and Purnanandam (2011).

Figure 1.2: Mortgage Originations by Types

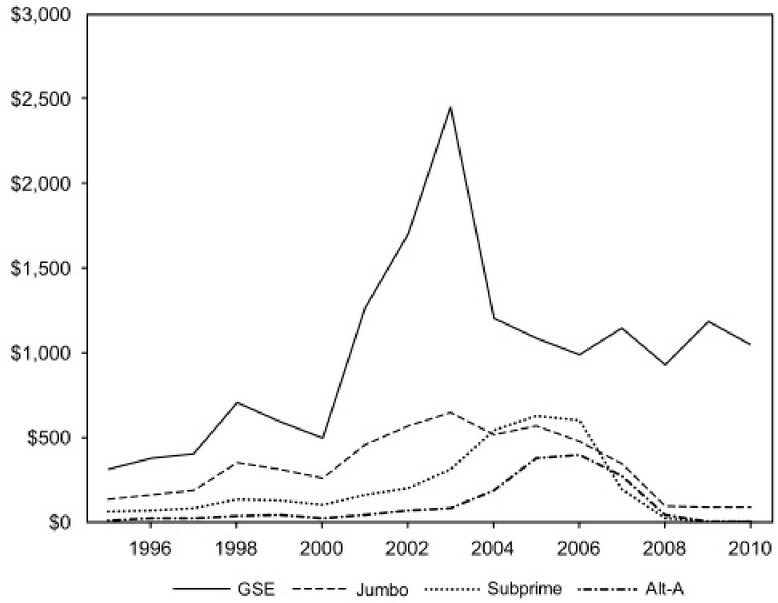


Fig. 4.1 Dollar volume of originations in GSE and private market

Source: Keys et al. (2013)

its balance sheet until maturity (denoted as the originate-to-hold (OTH) model) or sell the loan to competitive investors through securitization (the OTD model).[5]

There are two key features in this model. First, compared to investors in securitization markets, the bank favors immediacy of cash flows due to the availability of other investment opportunities or due to an agency-related incentive to compensate the bank manager based on realized cash flows. Second, compared to the lender, investors are disadvantaged in holding mortgages in the case of default due to their inability to renegotiate effectively with borrowers. When housing price expectations increase, the wedge in the value for immediacy for the bank overwhelms the impact of investors' inefficient holding of the loan through securitization. I show that increased housing price expectations enhance the attractiveness of securitization markets for the bank by transferring ownership of mortgage loans to investors through securitization.

[5]For tractability, I simplify the model by not allowing for partial holdings of any given mortgage or trenching as modeled in DeMarzo (2005). It is easy to show that incorporating these features only quantitatively alter the model predictions.

I further show that when investors' renegotiation disadvantage is not severe, selling off loans to investors through OTD is always desirable for the bank. In this case, investors value mortgages more than the bank does with or without default (thus, OTD dominates OTH). This is consistent with the fact that when the securitization market was dominated by government-sponsored enterprises (GSEs) such as Fannie Mae and Freddie Mac, starting in the 1980s, banks switched towards the OTD model gradually (Shin, 2009). Given the conservative lending standards mandated by the GSEs (conforming loans), extension of credit to subprime borrowers was not a major factor prior to 2000. In addition, in the absence of a house price boom, outside investors may have worried more about losses associated with contingent default. In this particular case, banks would not have preferred OTD to OTH outside the GSE market. Thus, the existence of securitization markets may not have further extended banks' risky lending without increased housing price expectations. This aligns with the fact that the long-existing securitization market for mortgage-backed securities, which began in 1970 with the founding of the Federal Home Loan Mortgage Corporation (Hill, 1996), did not cause any other crisis prior to 2007, even though securitization in the primary market had experienced steady growth since 1980 (Shin, 2009).

On the other hand, when investors' renegotiation disadvantage is severe compared to banks' desire of immediacy of cash, the securitization decision may depend on the future housing price. In particular, when housing price expectations are high enough, the associated probability of borrower default is low. Then, for investors, the loss in case of default will be dominated by the gain in case of solvency. The bank would, then, prefer to offload mortgages through OTD, as opposed to holding loans on its balance sheet and providing for costly regulatory capital. As the bank can sell mortgages to investors through OTD, it would offer loans to even riskier borrowers, who may not have been eligible for mortgages without securitization markets. In this case, securitization markets magnify banks' risky lending incentives, especially to subprime mortgage borrowers with low creditworthiness.[6]

[6]This is consistent with the fact that during the recent housing boom, the expansion of subprime mortgages is much faster than that of primary mortgages (Keys et al., 2012a).

Such extra credit expansion to lower-quality borrowers under the OTD model would raise ex post defaults if house prices decline. Lastly, I modify the basic model by incorporating agency misalignment in lending following Rajan et al. (2010), and, confirm that all results derived under symmetric information persist (and may even be quantitatively augmented) in the presence of asymmetric information.[7]

The model generates three major empirical predictions. First, in markets with higher housing expectations, more securitization is expected. Second, from an ex ante perspective, in markets with higher housing price expectations, banks with more OTD lending would extend loans to riskier borrowers. Third, from an ex post perspective, these banks would suffer greater defaults when housing prices decline. I test these hypotheses by using data from call reports and the Home Mortgage Disclosure Act (HMDA) database. In particular, I show that banks with more business in regions with higher housing price appreciation and with greater exposure to securitization markets expanded their lending more aggressively. Accordingly, these banks suffered a greater number of mortgage defaults when housing prices declined and/or when access to securitization opportunities vanished.[8]

My paper contributes to the literature in several ways. First, taking housing price expectations as the central role and using a model that explores the interaction effect of housing price expectations and banks' exposure to securitization markets, I can well explain three striking and co-existing patterns during 2000-2006, i.e., a peak in house prices, massive subprime mortgage lending, and booming securitization markets. In particular, I show that the emergence of securitization markets amplifies banks' incentives to make riskier loans when housing price expectations are higher. A stream of studies show how a housing bubble prior to 2007 substantially boosted credit expansions in the subprime market, leading to increased defaults when home prices started to drop in 2007.[9] However, other studies emphasizing

[7]the detailed results are presented in the Appendix A.1.

[8]Duchin and Sosyura (2014) show that banks with support from the Toxic Assets Repurchase Program (TARP) still extended mortgages to risky borrowers after 2008, even though selling the mortgages was difficult.

[9]A partial list includes Mian and Sufi (2009), Belsky and Richardson (2010), Demyanyk and Van Hemert (2011), Piskorski and Tchistyi (2011), and Nadauld and Sherlund (2013).

information asymmetry and incentive misalignment associated with the OTD model identify banks' reduced screening incentive, as a major reason for credit expansion in subprime markets.[10] To my knowledge, my paper is the first attempt to formally model the interaction effect of these two widely discussed factors. Meanwhile, my model also predicts less risky lending and unpopularity of securitization markets when housing price expectations are low, which is consistent with the facts prior to 2000.

Second, I show that the credit expansion and securitization boom can be explained in a very simple framework. Specifically, I show that even under a symmetric information setting, the presence of securitization markets can still amplify banks' riskier lending incentives, though agency misalignment may augment this effect. This finding complements to the existing literature about the impact of information asymmetry (e.g., Keys et al., 2010; Agarwal et al., 2012; Rajan et al., 2015), and also points out a fundamental aspect of riskiness associated with securitization that has been underappreciated to date.

Third, my model shows that banks' ex ante risky lending and subsequent mortgage defaults ex post can be both outcomes of rational behavior. Information frictions , heterogeneous beliefs (Chinco and Mayer, 2011; Xiong, 2013; Brunnermeier et al., 2014), or incentive factors, which existing studies rely on as the driving force behind the recent subprime mortgage crisis, may not be essential, though all these factors may quantitatively augment banks' riskier lending outcomes.

Fourth, this paper is broadly related to studies on securitization markets in general (DeMarzo and Duffie, 1999; DeMarzo, 2005; Axelson, 2007; Hartman-Glaser et al., 2012; Frankel and Jin, 2015), although my paper does not explore optimal security design. Finally, this paper is also related to work on boom-bust cycles with rational players (Persons and Warther, 1997; Zeira, 1999).

The rest of the paper is organized as follows. Section 2 presents the basic model un-

[10] Studies focus either on moral hazard(Keys et al., 2009, 2010; Rajan et al., 2010; Keys et al., 2012b; Demiroglu and James, 2012; Rajan et al., 2015) or on adverse selection (Downing et al., 2009; Agarwal et al., 2012; Jiang et al., 2013) associated with the OTD model.

der symmetric information. Section 3 analyzes a general case with asymmetric information. Section 4 discusses limitations and possible extensions of the model. Section 5 outlines the model's empirical implications. Section 6 presents empirical analyses and results. Conclusions and policy implications appear in Section 7.

1.2 Model

1.2.1 Model Setup

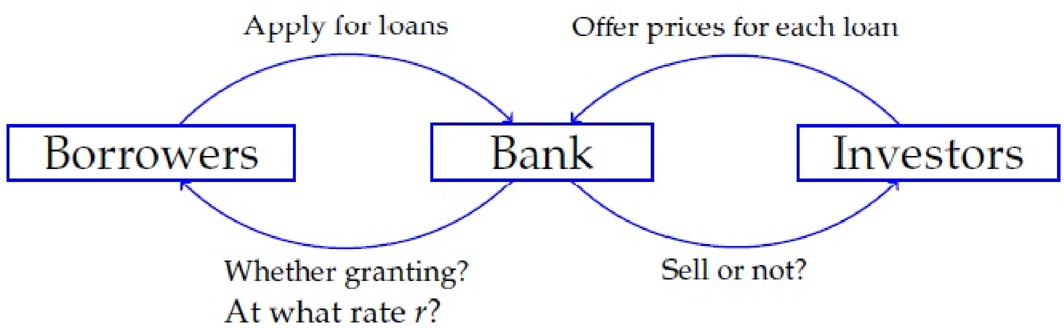
The model consists of three groups of risk-neutral players: borrowers, a lender (bank), and competitive investors.[11] There are two periods, $t = 0, 1$. At period $t = 0$, each borrower applies for a loan from the bank to purchase a house with fixed value P_0. Without loss of generality, I assume that the mortgage is a 100% loan, thus the amount borrowed from the bank equals P_0. The mortgage term consists of two periods, and the repayment is required in the next period $t = 1$.[12] If the lender approves the borrower's application, it will specify the mortgage repayment, M. The mortgage repayment includes both the principal, P_0, and the interest payment, i.e., $M = (1 + r)P_0$.

Denote the value of the house in the next period as P. Given the housing price fluctuation, P may be lower than P_0 (e.g. the housing price declines across periods). Then, the borrower may choose to default on the mortgage when P is low enough relative to the mortgage repayment M. This contingent default occurs whenever the borrower is better off giving up the house to the lender via foreclosure instead of fully paying off the mortgage. In this case, the cost borne by the borrower is smaller than the mortgage repayment M.

[11] Brueckner (2000) provides a simple and tractable framework discussing down payment and mortgage term choices in the presence of asymmetric information. I extend this model by introducing the securitization market, in which the lender (bank) can sell its mortgage loans to investors in the securitization market.

[12] Here, the two-period mortgage term excludes the option aspect of the mortgage default decision discussed in Deng et al. (2000). However, as discussed in Brueckner et al. (2012), extending the current mortgage term to a multiple-period term will only complicate the analysis and would not qualitatively change the model's implications. Qualitatively, the possibility of a house price recovery may make a borrower more reluctant to default, which leads to a higher threshold housing price for defaulting. Ex ante, the bank is willing to offer loans to borrowers with even lower creditworthiness.

Figure 1.3: Actions between Players



For any given borrower, there exists a future housing price threshold $\widetilde{P}$, under which the borrower defaults. This threshold depends on each borrower's default cost, denoted as C. As illustrated in Brueckner et al. (2012), such default costs can be viewed as the cost of credit impairment, moving costs, and any psychic costs from failing to honor the mortgage contract (Guiso et al., 2013).[13] In the literature, the role of default costs has been extensively studied (e.g. Brueckner, 2000; Foote et al., 2008, 2012). Default costs, C, are heterogeneous across borrowers, ranging from $\underline{C}$ to $\overline{C}$. When C is larger, the borrower loses more in case of default. Thus at any given house-price, the default is less attractive to her than another borrower with a lower C. Therefore, C is also a proxy for a borrower's creditworthiness, which plays a role in a borrower's optimal default decision. The model can be described in Figure 1.3.

Since each borrower is risk-neutral, assume that a borrower's utility function is

$$U = Y - \delta\left(-\int_0^{\widetilde{P}} C f(P, \mu_P) dP + \int_{\widetilde{P}}^{\infty} (P - M) f(P, \mu_P) dP\right) \tag{1.1}$$

where $f(P, \mu_P)$ is the probability density function for the housing price at $t = 1$. μ_P is a

[13] Alternatively, C can also be interpreted as a benefit of owning a house. In this instance, a resident who values the house more is less likely to default. Accordingly, this more reliable resident will be charged a lower mortgage payment.

mean shifter parameter, satisfying $F_{\mu_P}(P, \mu_P) < 0$, in which case the first-order stochastic dominance property holds. Following Brueckner et al. (2012), I use μ_P as an indicator for future housing price expectations. A larger μ_P indicates a larger probability that the housing price at $t = 1$ is higher, and vice versa. In this model, I assume that all players have the same housing price expectations and do not impose any heterogeneity in beliefs.[14]. I show that even without heterogeneous beliefs, the crisis is still possible.[15]

$\widetilde{P}$ represents the housing price trigger at which the borrower decides to default. Y denotes the exogenous component of wealth, which equals initial assets plus the discounted value of lifetime income. δ is the borrower's discount factor across time, $0 < \delta \geq 1$. Thus, a borrower makes her default decision to maximize her utility by choosing $\widetilde{P}$. Taking the derivative on Equation (1) with respect to $\widetilde{P}$, the first-order condition is

$$-Cf(\widetilde{P}, \mu_P) - (\widetilde{P} - M)f(\widetilde{P}, \mu_P) = 0 \tag{1.2}$$

thus,

$$\widetilde{P} = M - ClabelT3 \tag{1.3}$$

Therefore, default occurs whenever the future housing price is below $\widetilde{P}$ – i.e.,

$$P < M - C \tag{1.4}$$

Intuitively, in the case of default, the borrower suffers the default costs C without owning the house, and in the absence of default, the borrower fully pays the mortgage repayment M and keeps the house. Thus, $M - P$ represents the net cost of owning the house. When the latter dominates the former, paying off the mortgage incurs an even larger cost than simply defaulting. Therefore, default is optimal for the borrower whenever Inequality 1.4 holds.

[14](Heidhues and Kőszegi, 2010), different from this paper, documents that expectation differentials can also cause the subprime mortgage crisis

[15]In fact, introducing heterogeneous housing price expectations across borrowers and investors will augment the results.

Assume that each borrower's reservation utility of not having a house equals

$$\overline{U} = Y$$

In other words, a borrower applies for a mortgage to buy a house only if the expected value from buying the house with a mortgage is non-negative.[16]

$$U^H = -\int_0^{M-C} Cf(P, \mu_P)dP + \int_{M-C}^{\infty} (P - M)f(P, \mu_P)dP \geq 0 \tag{1.5}$$

which is a borrower's participation constraint.

Totally differentiating the borrower's binding IR constraint above, the relationship between M and C is given by

$$\frac{dM}{dC} = -\frac{U_C^H}{U_M^H} \tag{1.6}$$

where

$$\begin{aligned} U_C^H &= \frac{\partial U^H}{\partial C} \\ &= Cf(M - C, \mu_P) - \int_0^{M-C} f(P, \mu_P)dP - Cf(M - C, \mu_P) \\ &= -\int_0^{M-C} f(P, \mu_P)dP < 0 \end{aligned} \tag{1.7}$$

[16]This is just a normalization assumption.

and

$$
\begin{aligned}
U_M^H &= \frac{\partial U^H}{\partial M} \\
&= -Cf(M-C,\mu_P) + Cf(M-C,\mu_P) - \int_{M-C}^{\infty} f(P,\mu_P)dP \\
&= -\int_{M-C}^{\infty} f(P,\mu_P)dP < 0 \qquad (1.8)
\end{aligned}
$$

Thus,

$$\frac{d\overline{M}}{dC} < 0$$

where $\overline{M}$ represents the maximum mortgage payment that a borrower is willing to pay. It simply states that this maximum mortgage value is a decreasing function of her default costs (i.e., her creditworthiness). In particular, a borrower with lower default costs (a riskier borrower) will accept a higher mortgage repayment because she is more likely to default to avoid this repayment.

Assuming that default costs are observable, there is no private information about a borrower's type in the current model.[17] For each borrower with particular default costs C, the monopoly bank decides whether to approve the loan to the borrower and the mortgage repayment M, if approved, to maximize its expected profits. The bank has two options: either holding the loan on its balance sheet until maturity (denoted as Originate-to-Hold or OTH) or selling the loan to investors through the securitization market (denoted as Originate-to-Distribute or OTD).[18]

Assume that the bank funds loans through deposits, where the interest rate for deposits

[17]In reality, the borrower's creditworthiness can be approximately measured by her credit score. If such a measure is precise, it is close to the symmetric information case. Further, in the next section, I will show that even when private information is allowed, the results derived under symmetric information qualitatively persist.

[18]Here, for illustrative purpose, I simply assume that the bank either holds the loan or sells the loan fully. At the end of this section, I will relax this assumption by allowing an exogenous probability α that the loan is sold to investors and probability $1-\alpha$ that the loan is retained by the bank.

equals r_d. The bank's discount factor is $\eta < 1$, while competitive investors do not discount values across time. Here, η represents new investment opportunities with high returns encountered by the bank, following DeMarzo and Duffie (1999).[19]

In addition, another important assumption is that, in the case of default, the bank can sell the house at its full price P, while investors can recover only a fraction $\gamma < 1$ from selling the house. This assumption stems from a series of studies showing that, compared to mortgages held by a bank, securitized mortgages are harder to renegotiate and, thus, have a higher foreclosure rate (Piskorski et al., 2010; Agarwal et al., 2011; Ghent, 2011; Adelino et al., 2013).[20] When the borrower defaults, due to inability to renegotiate, investors only get γP if they buy the loan from the bank.

Then, if the bank offers a loan with repayment M to a borrower with default costs C, the bank's expected present value of profit by holding the loan until maturity is

$$\pi^{OTH} = -\eta(1 + r_d)P_0 + \eta \int_{0}^{M-C} Pf(P, \mu_P)dP + \eta \int_{M-C}^{\infty} Mf(P, \mu_P)dP \tag{1.9}$$

where the first term equals the discounted value of payment to depositors; the second term represents the expected value when the borrower defaults; and the last term is the expected value when the borrower does not default.

If the loan is sold to investors, the bank's expected present value of profit equals

$$\pi^{OTD} = -\eta(1 + r_d)P_0 + \int_{0}^{M-C} \gamma Pf(P, \mu_P)dP + \int_{M-C}^{\infty} Mf(P, \mu_P)dP \tag{1.10}$$

[19]This is a reduced form way to model the feature that comparing to investors in securitization markets, the bank values the immediacy of cash more. Thus η can be interpreted in many other ways. For example, an alternative interpretation, from compensation literature, is that the bank manager has incentives to "cash out" illiquid loans to boost up her short-term performance, as discussed in Bhattacharyya and Purnanandam (2012).

[20]Here, γ captures investors' disadvantage in renegotiation. I can instead assume that the bank also suffers a loss in case of default with a renegotiation parameter $\gamma' > \gamma$. This will not change the results. More generally, γ can also be interpreted as the service fees or other related efficiency costs caused by securitization in the case of default.

where the last two terms together are the price offered by competitive investors, which equals investors' expected value of the loan.

By comparing profits that the bank can get from OTH and OTD, the main tradeoff comes from the last two terms in Equations 1.9 and 1.10: 1) expected value in the case of default and 2) expected value when the default does not occur. For the latter case, OTD is always preferable because investors value the mortgage without time discount. For the former case, it depends on the relative magnitude of the bank's time discount factor η and investors' renegotiation discount γ. When $\eta \leq \gamma$, the value depreciation from holding the loan is larger than the value depreciation caused by the renegotiation barrier. In this case, even when default occurs, OTD is still more attractive than OTH, as the bank's expected profit from OTD is strictly larger than that from OTH. On the other hand, when $\eta > \gamma$, the expected profit differential between OTH and OTD will depend on the trade off between upside gains without default and downside losses in default. In this case, investors value the loan more if it does not default, but they value it less than the bank when default occurs. More intuitively and loosely speaking, if other things equal, with a larger time discount (i.e., a smaller η), the bank is less patient and is more willing to sell off mortgages. Alternatively, ceteris paribus, a larger renegotiation loss (i.e., a smaller γ), investors values mortgages less and thus the bank is more reluctant to choose OTD.

1.2.2 The Bank's Mortgage Lending Decisions

I will start with a simple case in which the bank holds loans that it offers. Then, for any given borrower with default costs C, the bank maximizes the present value of its expected profit by choosing M.

$$\max_{M} \pi^{OTH} = -\eta(1+r_d)P_0 + \eta \int_{0}^{M-C} Pf(P,\mu_P)dP + \eta \int_{M-C}^{\infty} Mf(P,\mu_P)dP \tag{1.11}$$

s.t.

$$\pi^{OTH} \geq 0 \tag{1.12}$$

and

$$U^H \geq 0 \tag{1.13}$$

Inequality 1.12 is the bank's participation constraint, indicating that by offering a loan, the bank earns nonnegative expected profits. Otherwise, the loan application will be rejected. Inequality 1.13 is the borrower's participation constraint, which means that a borrower applies for a mortgage only when the expected utility from doing so to own a house is at least the same as her reservation utility without owning a house.

The first-order condition of (11) is

$$-Cf(M-C,\mu_P) + \int_{M-C}^{\infty} f(P,\mu_P)dP = 0 \tag{1.14}$$

which determines $M^* = M(C)$ implicitly.

Proposition I.1. *A borrower's maximum willingness to pay for a mortgage, M, is negatively correlated to her creditworthiness, measured by her default costs, C.*

$$\frac{dM}{dC} < 0$$

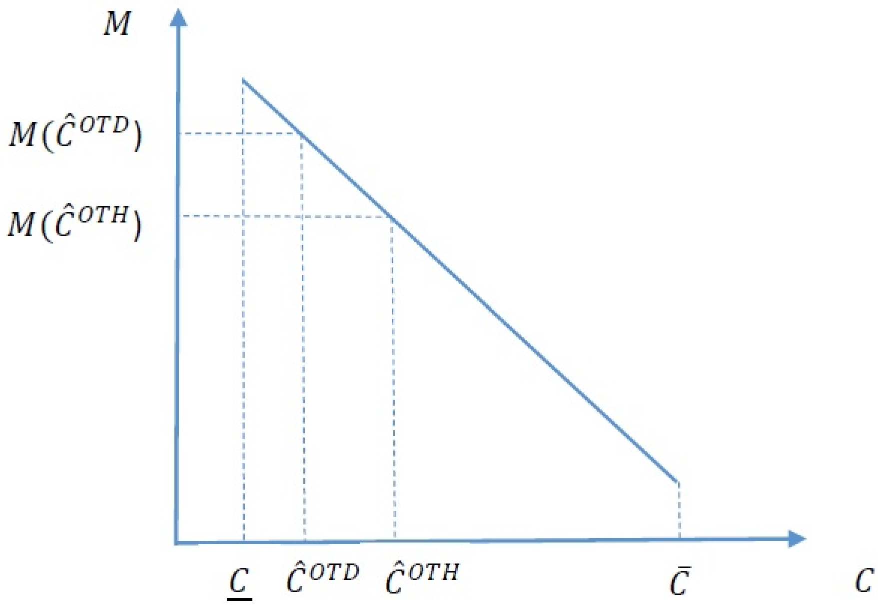
Proof. Totally differentiating the first-order condition in Equation 1.14 gives the result. □

Thus, the bank charges a lower mortgage payment (or equivalently a lower interest rate) for a borrower who is more creditworthy.[21] This negative relationship between the mortgage payment M and default costs C is illustrated in Figure 1.4.

Next, I show that the bank has incentives to lean towards OTD when housing price expectations increase. In particular, for any give type of borrowers, the profit wedge for

[21]Similar results apply to the case in which the bank sells the loan to investors, when replacing the bank's objective function with the expected profit under OTD.

Figure 1.4: Relationship between Mortgage Payment (M) and Default Costs (C)



the bank between OTD and OTH is increasing in housing price expectations. This result is summarized in the following Proposition.

Proposition I.2. *For a borrower with default cost C and mortgage payment $M(C)$, the profit wedge between OTD and OTH for the bank is increasing in the housing price expectation μ_P.*

Proof. Recall that the bank's profits from OTD and OTH, respectively, are

$$\pi^{OTD} = -\eta(1+r_d)P_0 + \int_0^{M(C)-C} \gamma P f(P,\mu_P)dP + \int_{M(C))-C}^{\infty} M(C)f(P,\mu_P)dP$$

$$\pi^{OTH} = -\eta(1+r_d)P_0 + \eta \int_0^{M(C)-C} P f(P,\mu_P)dP + \eta \int_{M(C)-C}^{\infty} M(C)f(P,\mu_P)dP$$

Thus the profit differential between these two cases are

$$\Delta\pi = (\gamma - \eta) \int_{0}^{M(C)-C} Pf(P, \mu_P)dP + (1-\eta) \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP \qquad (1.15)$$

I show that $\Delta\pi$ is increasing in μ_P by discussing two cases. First, when $\gamma \geq \eta$,

$$\begin{aligned} \Delta\pi &= (\gamma-\eta) \int_{0}^{M(C)-C} Pf(P, \mu_P)dP + (\gamma-\eta) \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP \\ &+ (1-\gamma) \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP \\ &= (\gamma-\eta)[\int_{0}^{M(C)-C} Pf(P, \mu_P)dP + \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP] \\ &+ (1-\gamma) \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP \end{aligned}$$

Since $F(P, \mu_P)$ satisfies the first-order stochastic dominance property, when μ_P is increasing, $\int_0^{M(C)-C} Pf(P, \mu_P)dP + \int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP$ is increasing and so does $\int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP$. Thus $\Delta\pi$ is increasing in μ_P.

Second, when $\gamma < \eta$, $\int_0^{M(C)-C} Pf(P, \mu_P)dP$ is decreasing in μ_P and $\int_{M(C)-C}^{\infty} M(C)f(P, \mu_P)dP$ is increasing in μ_P from the first-order stochastic dominance property. Thus from Equation 1.15, $\Delta\pi$ is increasing in μ_P. □

Therefore, for any borrower, the bank has stronger incentive towards OTD with higher housing price expectations. The intuition is straightforward: with a higher housing price expectation, it is more likely that the borrower does not default and thus a larger gain is expected for the bank to sell the mortgage to investors compared to holding the mortgage until it matures.

1.2.2.1 Subprime Lending

In this model, the extent of risky lending is determined by the worst borrower (i.e., the lowest default costs) to whom the bank grants a loan. The worst borrowers under OTH and OTD, respectively, are determined by

$$\pi^{OTH}(\widehat{M}^{OTH}, \widehat{C}^{OTH}) \geq 0 \tag{1.16}$$

and

$$\pi^{OTD}(\widehat{M}^{OTD}, \widehat{C}^{OTD}) \geq 0 \tag{1.17}$$

Denote $\widehat{C}^{OTH}$ and $\widehat{C}^{OTD}$ as values associated with the case in which the bank's expected profit equals zero under OTH and OTD, respectively. $\widehat{M}^{OTH} = M^{OTH}(\widehat{C}^{OTH})$ and $\widehat{M}^{OTD} = M^{OTD}(\widehat{C}^{OTD})$ are associated optimal mortgage payments. Then, $\widehat{C}^{OTH}$ and $\widehat{C}^{OTD}$ are the worst borrowers that the bank grants mortgages to. Borrowers with even lower default costs do not qualify for a mortgage.[22] Here, a reduction in $\widehat{C}$ indicates that the bank offers mortgages to some low-quality borrowers, who would not have been eligible for a mortgage before. According to Brueckner et al. (2012), such a reduction represents the expansion of subprime lending. In the following model, I offer a different perspective from Brueckner et al. (2012) and focus on the impact of the emergence of the OTD market on subprime lending. I show that when housing price expectations are above a threshold level, the bank with access to securitization markets extends subprime lending to even riskier borrowers than in the case of OTH.

Lemma I.3. *A higher housing price expectation leads the bank to extend suprime mortgage loans to riskier borrowers under both OTH and OTD i.e.,* $\frac{d\widehat{C}^{OTH}}{d\mu_P} < 0$, $\frac{d\widehat{C}^{OTD}}{d\mu_P} < 0$.

[22] At the same time, the bank needs to earn nonnegative profit from lending to the worst borrower–i.e., $\pi^{OTH}(\widehat{M}, \widehat{C}^{OTH}) \geq 0$ and $\pi^{OTD}(\widehat{M}, \widehat{C}^{OTD}) \geq 0$. From a borrower's perspective, she accepts the loan as long as $U^H(\widehat{M}, \widehat{C}) \geq 0$. I will focus on cases in which these two conditions hold. An alternate interpretation is that housing is essential; thus, a borrower will agree to the terms of a mortgage regardless of its cost. Then, the reservation utility of not owning a house approaches negative infinity, and, IR constraint never binds.

Proof. Taking the total differentiation of Equations 1.9 and 1.10 by setting zero expected profits,

$$\frac{d\widehat{C}^i}{d\mu_P} = -\frac{\pi^i_{\mu_P}}{\pi^i_C} < 0 \text{ where } i = \{OTH, OTD\} \tag{1.18}$$

□

This is consistent with Proposition 1 in Brueckner et al. (2012), in which the authors show that with a higher housing price expectation, a bank is willing to lend to riskier borrowers when the bank itself holds the mortgage. This pattern is also true when the bank sells the loan to investors.

Corollary I.4. *The lowest default costs with which a borrower can be granted a loan by the bank is increasing with the bank's funding costs, the interest rate of bank deposits. That is,* $\frac{d\widehat{C}^i}{dr_d} > 0$ *for* $i = \{OTH, OTD\}$*.*

These comparative statics are straightforward. When the bank's funding cost decreases (lower interest rate r_d), it will be more aggressive in extending its lending. This is consistent with the housing market boom during 2000-2007. Specifically, after the dot-com bubble collapsed in early 2000s, the Federal Reserve lowered the interest rate to stimulate the economy and, in turn, may have contributed to the credit expansion via the subprime mortgage market (Keys et al., 2012a).[23]

Another important feature worth pointing out is that the profit wedge between OTD and OTH is an increasing function in terms of mean shifter μ_P, formally stated in the following Proposition.

Proposition I.5. *Securitization incentive is an increasing function of the housing price expectations* μ_P*.*

Proof. The result can be derived by simply differentiating the profit wedge between OTD and OTH. □

[23] As discussed in Dell'Ariccia et al. (2014), interest rate can be a policy tool to regulate banks' risky lending.

The intuition is very simple, when housing price expectations are higher, the chance of default of any given mortgage is lower, thus both the bank and investors value the mortgage more. However, since investors do not suffer the time discount as the bank does, gains from enhanced chance that mortgages are fully paid are higher than those for the bank from OTH.

Next, I show that under certain conditions, $\widehat{C}^{OTD} < \widehat{C}^{OTH}$. That is, the bank extends subprime mortgage lending to lower-quality borrowers under OTD than that under OTH. Instead of fully deriving the mortgage payment function in terms of default cost $M^* = M(C)$, I derive conditions under which the lender gets positive benefit under OTD with $(\widehat{M}^{OTH}, \widehat{C}^{OTH})$, that is, the mortgage payment for the worst borrower under OTH. In such a case, the bank can extend loans to a borrower with even worse creditworthiness and still earn positive expected profit by doing so through OTD, thus extending lending to even riskier borrowers than that through OTH. These conditions can be summarized by the following inequality.

$$\begin{aligned}
& \int_0^{M(\widehat{C})-\widehat{C}} \gamma P f(P, \mu_P) dP + \int_{M(\widehat{C})-\widehat{C}}^{\infty} M(\widehat{C}) f(P, \mu_P) dP \\
\geq \; & \eta \int_0^{M(\widehat{C})-\widehat{C}} P f(P, \mu_P) dP + \eta \int_{M(\widehat{C})-\widehat{C}}^{\infty} M(\widehat{C}) f(P, \mu_P) dP \\
= \; & \eta(1 + r_d) P_0
\end{aligned}$$

The first inequality is equivalent to

$$(\gamma - \eta) \int_0^{M(\widehat{C})-\widehat{C}} P f(P, \mu_P) dP + (1 - \eta) \int_{M(\widehat{C})-\widehat{C}}^{\infty} M(\widehat{C}) f(P, \mu_P) dP \geq 0 \qquad (1.19)$$

where the first term captures the net expected benefit from switching from OTH to OTD when default occurs, and the second term captures the net expected benefit in the case of no default. Clearly, if $\gamma \geq \eta$, the bank gains more expected profits in OTD than in OTH both with or without default. Thus, OTD is strictly preferred.

Lemma I.6. *When investors' renegotiation discount factor is larger than the bank's time discount factor, that is, $\gamma \geq \eta$, the bank's subprime lending through OTD is always more aggressive than that through OTH i.e., $\widehat{C}^{OTD} < \widehat{C}^{OTH}$, irrespective of μ_P.*

When $\gamma < \eta$, the preference between OTD and OTH is intermediated by the expectations about future housing price. This is the case presented below.

Proposition I.7. *When investors' renegotiation discount factor is smaller than the bank's time discount factor, $\gamma < \eta$, there exists a threshold housing price expectation, $\overline{\mu_P}$, such that when the housing price expectation is above this threshold, the bank extends lending to riskier borrowers when it adopts an OTD model. That is,*

$$\widehat{C}^{OTD} < \widehat{C}^{OTH} \ \textit{if}\ \mu_P > \overline{\mu_P} \tag{1.20}$$

$$\widehat{C}^{OTD} \geq \widehat{C}^{OTH} \ \textit{if}\ \mu_P < \overline{\mu_P} \tag{1.21}$$

where $\overline{\mu_P}$ satisfies

$$\frac{\int_{M(\widehat{C})-\widehat{C}}^{\infty} M(\widehat{C}) f(P, \overline{\mu_P}) dP}{\int_{0}^{M(\widehat{C})-\widehat{C}} P f(P, \overline{\mu_P}) dP} = \frac{\eta - \gamma}{1 - \eta} \tag{1.22}$$

Proposition I.7 holds since $F(P, \mu_P)$ satisfies the first-order stochastic dominance property, $F_{\mu_P}(P, \mu_P) < 0$. This proposition shows that OTD by itself does not necessarily extend mortgage credit to worse-quality borrowers than OTH does. Whether OTD worsens the situation compared to OTH depends on how players in the economy think about future housing prices. When the expected housing price at $t = 0$ is below a threshold, OTD is not attractive because it is more likely that the house price is low at $t = 1$, and default is more likely to occur. Then, the net loss from OTD with a larger default probability will dominate the net gain from OTD with a smaller chance of survival. In this case, low housing price expectations lead the bank to more conservative lending with OTD compared to OTH. This is a possible explanation for why securitization markets did not cause any crisis in the past. On the other hand, when $\mu_P > \overline{\mu_P}$ – i.e., the expected future housing price is high enough– the net gain in survival dominates the net loss in default, and, thus, OTD is preferred and a greater number of risky borrowers are offered loans under OTD.

Corollary I.8. *When $\gamma < \eta$, for a given borrower's type $\widetilde{C}$, denote $\widetilde{\mu_P}^{OTD}$ and $\widetilde{\mu_P}^{OTH}$ corresponding least housing price expectations which guarantee the bank offers the loan this borrower. Then, these housing price expectations satisfy*

$$\widetilde{\mu_P}^{OTD} < \widetilde{\mu_P}^{OTH} \tag{1.23}$$

Proof. $\widetilde{C}$ is the worst borrower, thus,

$$\int_0^{M(\widetilde{C})-\widetilde{C}} \gamma P f(P, \widetilde{\mu_P}^{OTD}) dP + \int_{M(\widetilde{C})-\widetilde{C}}^{\infty} M(\widetilde{C}) f(P, \widetilde{\mu_P}^{OTD}) dP = \eta(1+r_d)P_0$$

$$\eta \int_0^{M(\widetilde{C})-\widetilde{C}} P f(P, \widetilde{\mu_P}^{OTH}) dP + \eta \int_{M(\widetilde{C})-\widetilde{C}}^{\infty} M(\widetilde{C}) f(P, \widetilde{\mu_P}^{OTH}) dP = \eta(1+r_d)P_0$$

Since $\gamma < \eta$, and $\widetilde{\mu_P}^{OTD}, \widetilde{\mu_P}^{OTH} > \overline{\mu_P}$,

$$\begin{aligned} & \int_0^{M(\widetilde{C})-\widetilde{C}} \gamma P f(P, \widetilde{\mu_P}^{OTH}) dP + \int_{M(\widetilde{C})-\widetilde{C}}^{\infty} M(\widetilde{C}) f(P, \widetilde{\mu_P}^{OTH}) dP \\ > \; & \eta \int_0^{M(\widetilde{C})-\widetilde{C}} P f(P, \widetilde{\mu_P}^{OTH}) dP + \eta \int_{M(\widetilde{C})-\widetilde{C}}^{\infty} M(\widetilde{C}) f(P, \widetilde{\mu_P}^{OTH}) dP \end{aligned}$$

Combined with $\pi_{\mu_P}^{OTD} > 0$, the result is as stated. $\square$

This is an immediate result from Proposition I.7 above. When a low-quality borrower (with relatively high default risk) applies for a mortgage, she only gets the bank's approval when housing price expectations are high enough. The break-even housing price expectation under OTD is lower than under OTH, which means that the bank has a weaker lending standard under OTD than under OTH.

Corollary I.9. *The threshold of housing price expectation is increasing in the bank's time discount factor η and is decreasing in investors' renegotiation discount factor γ. That is,* $\frac{d\overline{\mu_P}}{d\eta} > 0$, $\frac{d\overline{\mu_P}}{d\gamma} < 0$

Proof. The left-hand side of Equation 1.22 is an increasing function of $\overline{\mu_P}$. The right-hand side is increasing in η and decreasing in γ. Thus, a larger η (or a smaller γ) needs a larger $\overline{\mu_P}$ to balance the equation. □

Intuitively, OTD through securitization markets is more attractive when the outside investment opportunities are better (i.e., lower η).To be specific, during economic booms, outside investment opportunities are more profitable. Thus banks have stronger desire to "cash out" mortgages for reinvestment. On the other hand, during economic recessions, the popularity of securitization markets is lessened. This is consistent with empirical evidence on endogenous choice of securitization over the business cycle found in Chernenko et al. (2014). Meanwhile, when securitized mortgages are easier to renegotiate (i.e., higher γ), investors value mortgages more and thus are willing to offer higher prices to banks. When renegotiations are harder, securitization markets will only be preferable with higher housing price expectations. This aligns with the surge of private label securitizations prior to the 2007-09 mortgage crisis (Keys et al., 2012a).

1.2.2.2 The Bank's Profits

Next, I compare the bank's total expected profits from their lending decisions under OTH and OTD. The result is summarized in the following Proposition.

Proposition I.10. *When $\widehat{C}^{OTD} < \widehat{C}^{OTH}$, the bank earns higher total expected profits under*

OTD than under OTH,

$$\Pi^{OTD} > \Pi^{OTH} \tag{1.24}$$

where

$$\Pi^i = \int_{\underline{C}}^{\overline{C}} \mathbb{1}^i(C)\pi^i(C)g(C)dC \tag{1.25}$$

$i \in \{OTH, OTD\}$.

Proof. Re-write Π^{OTD} and Π^{OTH} as follows:

$$\begin{aligned}
\Pi^{OTD} &= \int_{\underline{C}}^{\widehat{C}^{OTH}} \mathbb{1}^{OTD}(C)\pi^{OTD}(C)g(C)dC + \int_{\widehat{C}^{OTD}}^{\widehat{C}^{OTH}} \mathbb{1}^{OTD}(C)\pi^{OTD}(C)g(C)dC \\
&\quad + \int_{\widehat{C}^{OTH}}^{\overline{C}} \mathbb{1}^{OTD}(C)\pi^{OTD}(C)g(C)dC \\
&= \int_{\widehat{C}^{OTD}}^{\widehat{C}^{OTH}} (C)\pi^{OTD}(C)g(C)dC + \int_{\widehat{C}^{OTH}}^{\overline{C}} (C)\pi^{OTD}(C)g(C)dC
\end{aligned}$$

$$\begin{aligned}
\Pi^{OTH} &= \int_{\underline{C}}^{\widehat{C}^{OTH}} \mathbb{1}^{OTH}(C)\pi^{OTH}(C)g(C)dC + \int_{\widehat{C}^{OTH}}^{\overline{C}} \mathbb{1}^{OTH}(C)\pi^{OTH}(C)g(C)dC \\
&= \int_{\widehat{C}^{OTH}}^{\overline{C}} (C)\pi^{OTH}(C)g(C)dC
\end{aligned}$$

When $\widehat{C}^{OTD} < \widehat{C}^{OTH}$, as discussed before, $\pi^{OTD}(C) \geq \pi^{OTH}(C)$ for any $C \geq \widehat{C}^{OTH}$. Thus

$$\int_{\widehat{C}^{OTH}}^{\overline{C}} (C)\pi^{OTD}(C)g(C)dC > \int_{\widehat{C}^{OTH}}^{\overline{C}} (C)\pi^{OTH}(C)g(C)dC$$

Therefore,

$$\Pi^{OTD} > \Pi^{OTH}$$

□

The profit differentials stem from two sources. First, for any given mortgage issued in either case, the expected profit from OTD is larger than that from OTH. Second, under OTD, the bank extends loans to some risky borrowers who could not qualify for mortgages under OTH. These additional issuances also contribute to the bank's profit. In this case, the bank is better-off ex-ante under OTD than under OTH.

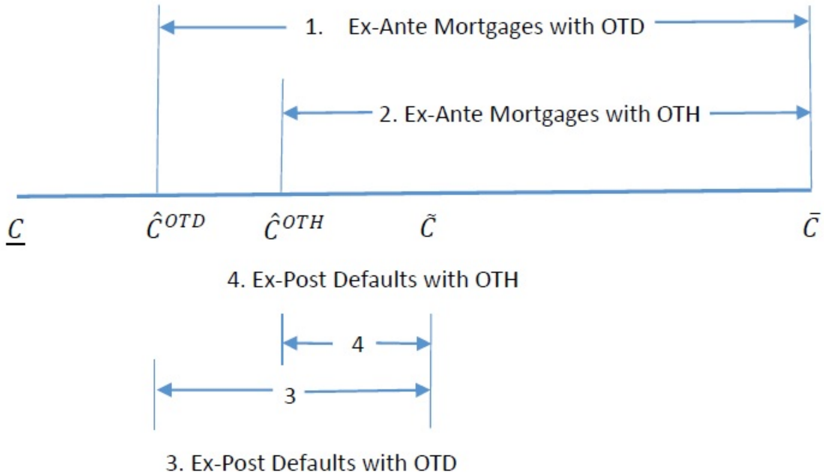
1.2.2.3 Ex Post Defaults

Next, I evaluate the possible implications from the ex post perspective. Denote the realized house price at $t = 1$ as P_1; then, there exists a threshold C_1, such that $P_1 = M(C_1) - C_1$, and all borrowers with default costs under C_1 (i.e., $C \leq C_1$) default. If the ex ante housing price expectations are high enough (i.e., $\mu_P \geq \overline{\mu_P}$), then the bank with OTD issues more loans to risky borrowers than those with OTH–i.e., $\widehat{C}^{OTD} < \widehat{C}^{OTH}$. When a low housing price is realized, we observe more ex post defaults under OTD, because the bank extends loans to riskier borrowers than under OTH. These low-quality borrowers, who cannot get loans under OTH, obtain loans from the bank under OTD, leading to greater ex post defaults.

Proposition I.11. *When $\mu_P > \overline{\mu_P}$, for any realized price P_1, more defaults occur under OTD than those under OTH. Those defaulted mortgages are the ones from borrowers with creditworthiness satisfying $C \leq C_1$.*

The ex ante credit expansion versus ex post defaults under OTD versus OTH is illustrated in Figure 1.5. Here, I focus on the case in which $\widehat{C}^{OTD} < \widehat{C}^{OTH}$. As shown in the graph, ex ante, when housing price expectations are high enough, the bank under OTD offers loans to riskier borrowers (Region 1) than under OTH (Region 2). When the housing price P_1 is realized ex post at $t = 1$, borrowers worse than C_1 default. Under OTD, the bank lends to more low-quality borrowers; thus, more defaults (Region 3) are observed than under OTH

Figure 1.5: Ex Ante Subprime Mortgage Credit Expansion and Ex Post Default



(Region 4).

In my model, as discussed above, all players make ex ante rational decisions. In this framework, the bank and investors do take the possibility of a housing price decline into account when they make their lending and investing decisions. As long as this possibility is small enough, the bank and investors expect to benefit from offering loans to riskier borrowers. In turn, this automatically leads to more ex post defaults, which are caused by a low realized housing price at $t = 1$.[24]

1.2.2.4 A More General Case

In previous sections, I focus on two extreme cases: 1) holding all mortgage loans on the bank's balance sheet (OTH); and 2) selling off all mortgage loans through the securitization market (OTD). In reality, however, it is common that banks retain some mortgage loans on their balance sheets and sell others to investors through securitization or use trenching to "skin in the game". I show in this section, that adding the feature by allowing the bank to retain a fraction of the loans it issues will not qualitatively alter the results derived so far. However, the magnitude of the bank's exposure to the securitization market, measured by

[24] In this static setting, I interpret housing price expectations as a rational belief of every player in the economy and illustrate that even without irrational beliefs, a crisis is possible.

the proportion of loans that are sold to investors, does quantitatively affect the conclusions reached above. Intuitively, when the bank is exposed more to the securitization market by selling off more loans to investors and retaining less on its balance sheet, its lending behavior is closer to the 100% OTD case. On the other hand, when the bank is exposed less to the securitization market, its behavior is closer to that under OTH.

I assume that for each mortgage loan, there is probability α that the loan is sold to investors through securitization and, $1 - \alpha$ that the bank retains the mortgage. As Rajan et al. (2010) point out, it is common in the residential mortgage market for securitizers to randomly select loans from a bank's portfolio in every risk category. As a result, for any loan, there exists a positive probability that the bank must retain the loan on its own balance sheet. Then, the lender's objective function becomes a weighted average of profit under OTD and under OTH as follows:

$$\pi = \alpha \pi^{OTD} + (1 - \alpha)\pi^{OTH} \tag{1.26}$$

where π^{OTD} and π^{OTH} are the expected profits from OTD and OTH, as defined above.

Proposition I.12. *When $\gamma < \eta$ and $\mu_P > \overline{\mu_P}$, the worst-quality borrower (represented by $\widehat{C}$) that the bank is willing to lend to satisfies*

$$\widehat{C}^{OTD} < \widehat{C} < \widehat{C}^{OTH} \tag{1.27}$$

In addition, the bank's willingness to extend credit increases with the prbability of the loan being sold, that is,

$$\frac{d\widehat{C}}{d\alpha} < 0 \tag{1.28}$$

Proof. For any C, when $\gamma < \eta$ and $\mu_P > \overline{\mu_P}$, I show $\pi^{OTD} > \pi^{OTH}$; thus,

$$\frac{d\pi}{d\alpha} > 0$$

For any $\alpha \in (0,1)$,

$$\pi(\widehat{C}^{OTH}) > \pi^{OTH}(\widehat{C}^{OTH})$$

and

$$\pi(\widehat{C}^{OTD}) < \pi^{OTD}(\widehat{C}^{OTD})$$

These two inequalities together give Inequality 1.27

Moreover,

$$\begin{aligned}
\frac{d\widehat{C}}{d\alpha} &= \frac{\partial \widehat{C}}{\partial \pi}\frac{\partial \pi}{\partial \alpha} \\
&= \frac{\frac{\partial \pi}{\partial \alpha}}{\alpha \frac{\partial \pi^{OTD}}{\partial \widehat{C}} + (1-\alpha)\frac{\partial \pi^{OTH}}{\partial \widehat{C}}} \\
&< 0
\end{aligned}$$

□

The intuition for Proposition I.12 is simple: when the housing price expectation is large enough, OTD brings more expected profits to the bank than OTH does. When the chance of selling loans to investors through OTD is larger (i.e., larger α), the bank can earn more profits. Thus, the bank's incentive to extend loans to riskier borrowers will be stronger. Accordingly, the default costs of the worst-quality borrowers who are offered loans will be smaller (lower $\widehat{C}$). In extreme cases, when $\alpha \to 1$, $\widehat{C} \to \widehat{C}^{OTD}$, while when $\alpha \to 0$, $\widehat{C} \to \widehat{C}^{OTH}$.

1.2.2.5 Allowing for Bank Competition

"*As long as the music is playing, you've got to get up and dance.*"

–Charles O. Prince, July 2007 at the *Financial Times*

Previously, I have discussed the case of a monopoly bank in the economy. Now I relax this assumption by assuming that there are two banks competing for mortgage borrowers and each bank offers an interest rate on the mortgage, r (equivalent to competing on M). Assume that, initially, neither bank has access to the securitization market. Thus, this is a classical Bertrand competition case and the equilibrium is symmetric. In equilibrium, for any given C, each bank offers $M^{OTH}(C)$ such that each bank's expected profit from the loan is zero. In this case, due to competition, loans are extended to borrowers with worse quality than that with only a monopolist bank.

Lemma I.13. *Without securitization markets, bank competition worsens the mortgage pool.*

$$\widehat{C}^{OTH}_{Comp} < \widehat{C}^{OTH}_{Mono} \tag{1.29}$$

where $\widehat{C}^{OTH}_{Comp}$ *represents default costs of the worst subprime borrower under bank competition and* $\widehat{C}^{OTH}_{Mono}$ *represents default costs of the worst subprime borrower with a monopoly bank.*

Competition transfers benefits from banks to borrowers, reducing banks' expected profit towards zero. Thus, riskier borrowers who would not get loan with a monopoly bank are offered loans. Now suppose that a securitization market opens. If only one bank can access the securitization market, we know that the bank can offer the borrower a mortgage payment lower than $M^{OTH}(C)$, such as $M^{OTH}(C) - \varepsilon$ and obtains the entire market share. Accordingly, the bank with access to the securitization market earns a positive expected profit and its competitor earns zero expect profit. Given this, if the competitor bank is not restricted from accessing the securitization market, it will also choose to sell loans in the securitization market. Then, a new equilibrium is achieved under another symmetric Bertrand competition with mortgage payment $M^{OTD}(C)$, which is determined by

$$-\eta(1 + r_d)P_0 + \int_{0}^{M-C} \gamma P f(P, \mu_P)dP + \int_{M-C}^{\infty} M f(P, \mu_P)dP = 0 \tag{1.30}$$

for every C. In the new equilibrium, each bank again earns zero expected profit and borrowers enjoy all the net benefits. In contrast to the case of the monopoly bank, more risky borrowers with even lower creditworthiness are granted loans. The results are summarized in the following Proposition.

Proposition I.14. *When there are two banks in the economy competing for mortgage payment M for each borrower, then, if $\gamma < \eta$ and $\mu_P > \overline{\mu_P}$, both banks sell their loans through OTD. At the same time, the worst borrower $\widehat{C}^{OTD}_{Comp}$ who gets the loan is worse than that in the single-bank case – i.e.,*

$$\widehat{C}^{OTD}_{Comp} < \widehat{C}^{OTD}_{Mono}$$

High housing price expectations increase each bank's risky lending incentive, and bank competition makes the incentive even stronger. Meanwhile, bank competition transfers benefits from banks to borrowers, lowering the mortgage payment for any borrower. This, in turn, allows some borrowers who could not get loans from a monopoly bank to now get the loans. Therefore, bank competition makes subprime mortgage lending even more aggressive.[25] Frankel and Jin (2015) model competition between a local bank and a remote bank, in which the local bank has information advantage about borrowers' types. They also provide a rationale that access to securitization market is an outcome of bank competition by showing that with securitization markets, the remote bank is able to compete with the local bank. This is similar to the point in my model: banks choose securitization to compete "efficiently" with each other.

1.3 Subprime Lending with Asymmetric Information

In the previous section, I showed that originate-to-distribute (OTD) through the securitization market amplifies the effect of high housing price expectations on reducing the lending standard to extend mortgage credit to risky borrowers. When housing price expectations are high enough, under OTD, the bank offers loans to low-quality borrowers who could not ob-

[25] On the other hand, since borrowers enjoy lower mortgage payments due to bank competition, their default incentives are weakened. Accordingly, bank competition may not incur more ex post defaults compared to the monopoly bank case.

tain mortgages under OTH. This result can be obtained even without introducing frictions such as information asymmetries. The main driving force is trade-offs between 1) "value enhancement" in case of no default, where investors value a mortgage more than the bank does, and 2) "value destruction" when default occurs, in which investors value a mortgage less than the bank does due to renegotiation inefficiency.

In this section, I prove that allowing for asymmetric information may augment the results derived in the symmetric information case above. The intuition is relatively straightforward and can be illustrated in two possible ways. The adverse selection story tells us that if the bank has private information about borrowers' type, while investors do not, the bank always wants to sell investors low-quality loans (i.e., low C) with high default probability. In turn, investors anticipate this and value loans sold to them less. However, when housing price expectations are high enough, investors' tolerance for low-quality loans increases, and thus, the bank offers loans to even lower-quality borrowers and then sells them to investors. Alternatively, if risky mortgages come from the bank's lack of incentive to screen borrowers when it can sell these loans to investors through securitization, the laxity in screening is aggravated when housing price expectations are high. Under high housing price expectations, investors again value risky loans more for their increased "survival likelihood." In response to this, the bank's screening incentive declines even further. This may augment the bank's risky lending incentive compared to the symmetric information case. Following Rajan et al. (2010), I model the bank's laxity in screening borrowers when it can sell loans in securitization markets and show that, in such a case, some low-quality borrowers, who cannot get loans in the symmetric information case, are granted loans by the bank and some high-quality borrowers, who are supposed to get loans, may be rejected by the bank. These two effects together result in a even worse average mortgage quality compared to the symmetric information case. Furthermore, I show that when housing price expectations increase, these inefficiencies are exaggerated. The detailed formulation can be found in the Appendix A.1.

1.4 Robustness and Extensions

My model captures interactions between housing price expectations and access to the securitization market and their possible impacts on subprime mortgage lending and ex post mortgage defaults. Different from Agarwal et al. (2012) and other studies, discussions in my model are based on bank level rather than loan level. For tractability, this simple and stylized model assumes away some important features of the subprime mortgage market during 2000-2006. These features may be key to subprime mortgage lending decisions and, thus, may play a role in ex post defaults, contributing to the subprime mortgage crisis in 2007-09. First, I assume the mortgage is a 100% loan with fixed interest, without down payment choice or choices on mortgage terms. Second, forced defaults, in which borrowers are unable to make mortgage payment on time due to insufficient income, are not modeled. Third, a fixed mortgage size is assumed in my model and borrowers cannot choose house values when applying for mortgages. Fourth, I do not introduce the possibility that banks may sell only worst loans to securitizers due to adverse selection. Lastly, potential feedback effects of mortgage lending on housing price are not captured by my model. In this section, I briefly discuss possible impacts of these features and how they may affect my results.

1.4.1 Down Payments and Mortgage Choices

In the current model, I assume that the mortgage is a 100 percent loan without down payment, and that the mortgage is a fixed-rate mortgage with interest payment rP_0. In reality, both initial down payments and mortgage terms can be chosen. According to some studies (Corbae and Quintin, 2015; Campbell and Cocco, 2015), low down payments and adjusted-rate mortgages (ARM) that allowed borrowers to postpone payments became especially popular among subprime mortgage borrowers with low creditworthiness. These changes could also have contributed to the crisis. However, these arguments are controversial. Foote et al. (2008) find that the popularity of ARMs among subprime mortgage borrowers did not necessarily result in more defaults when compared with FRMs. Theoretically, even though these factors play a role in subprime mortgage lending, as discussed in Piskorski and Tchistyi (2010) and Brueckner et al. (2015), incorporating these factors into my model may not qualitatively alter the results. When housing price expectations are high, ARMs and low down payments are not only attractive to less creditworthy borrowers, but these mortgages are also more acceptable to both the bank and investors, which will further extend lending to riskier borrowers. Because investors value loans more than the bank under high housing price expectations, through OTD, the subprime mortgage credit expands more aggressively than through OTH, which is consistent with predictions in my model. On the other hand, low down payments and ARMs allow borrowers to postpone mortgage payments, and ex post defaults are more likely. Taking all of this into account, introducing down payment and ARMs may weaken my results quantitatively, but the results will be qualitatively similar.

1.4.2 Forced Default

This model is built mainly on borrowers' optimal default choice by linking borrowers' quality to housing prices relative to mortgage payments. In fact, low-quality borrowers are not only those with low default costs, but they are also more likely to be the ones with lower incomes who have a higher chance of being unable to make payments on time (Campbell and Cocco, 2015). When payment requirements cannot be met, forced defaults occur. In other words, given the same mortgage terms, low-quality borrowers are more likely to default both voluntarily and compulsorily. Taking the forced default issue into account, a mortgage for a lower-quality borrower will be valued less. Then, a higher threshold of housing price expectation, $\overline{\mu_P}$, is needed for the bank to prefer OTD to OTH compared to the benchmark case without forced defaults.

1.4.3 Variable Mortgage Size

My model assumes that every borrower applies for a mortgage loan of the same size, P_0. Borrower quality then depends solely on default costs. When borrowers are allowed to choose mortgage size, the income-to-value ratio (ITV) (which determines the affordability of each loan to a borrower), may be another dimension for measuring mortgage quality. A loan with a smaller income-to-value ratio (ITV) is more likely to be granted when housing price expectations are high. In this general case, one would not only observe that loans are extended to low-quality borrowers, but one would also expect more loans with smaller ITVs. Again, when housing price expectations are high enough access to securitization markets makes these effects even stronger.

1.4.4 Adverse Selection of Securitized Mortgages

In the model, I ignore the possibility that the bank may choose which loans to sell to investors through securitization. If the bank has this choice, it may be the case that low quality loans are sold to investors, as in Parlour and Plantin (2008) and Frankel and Jin (2015). Investors would take this adverse-selection effect into account and offer lower prices for securitized loans. This, in turn, may restrict the bank's lending to risky borrowers. However, when housing price expectations are high, investors are more tolerant of low-quality loans given that the expected default probability decreases. Such tolerance, in turn, boosts the bank's incentive to lend to lower quality borrowers. Higher exposure to securitization markets, therefore, enhances the banks incentives to lend to riskier borrowers. Therefore, predictions from the main model persist as long as housing price expectations are high enough.[26] As pointed out in Rajan et al. (2010), for mortgaged-backed securities, securitizers randomly select loans from a bank's portfolio in every risk category to avoid the potential adverse selection.

1.4.5 Feedback Effects of Mortgage Lending on Housing Prices

Under a static setting, my model cannot capture possible dynamic effects, such as the option value of a mortgage, nor can the model capture potential feedback effects of mortgage

[26] As discussed, the emergence of adverse selection may lead to a higher threshold of housing price expectations $\overline{\mu_P}$ than the benchmark case in the absence of adverse selection.

lending on housing prices, as discussed in Campbell and Cocco (2015). If extensive subprime mortgage lending further enhances housing prices, we would expect that mortgage credit expansion would lead to even higher housing price expectations. This would only futher lower the bank's lending standard. On the other hand, when housing prices decline, more defaults would be observed. Consequently, the bank may cut back on lending, which would result in an even lower housing price and a more pessimistic view about future housing prices. If this was the case, these feedback effects would act as an "accelerator" to amplify boom-bust patterns. In a related context, Persons and Warther (1997) develop a dynamic model of adoption of financial innovations and show that feedback effects may have substantial impacts on boom-bust cycles. I plan to explore such a factor in the future.

1.5 Empirical Implications

Several features of the recent subprime mortgage crisis in the U.S. are consistent with my model's predictions and I summarize them below.

1.5.1 Housing Price Expectations and Subprime Mortgage Lending

The model in this paper predicts the positive impact of housing price expectations on subprime mortgage lending.[27] In particular, high housing price expectations weaken borrowers' default incentives, reducing possible losses caused by borrowers' contingent default decisions. Moreover, even in the case of involuntary default, a high housing price permits the bank and investors to recover greater value from selling the house. Therefore, with high housing price expectations, the bank and investors are more tolerant of riskier borrowers. Brueckner et al. (2012) find supporting evidence on this.

[27] Brueckner et al. (2012) have a similar prediction.

1.5.2 Endogenous OTD Market Emergence

Though the model presented in this paper is static, the main trade-off between the bank's time discount factor η and investors' renegotiation discount factor γ sheds light on the possible endogenous emergence of an OTD model of lening. To be specific, the comparative statics of η and γ on the threshold of housing price expectation $\overline{\mu_P}$ indicate that the use of securitization is liekly to be pro-cyclical. During economic booms, the bank encounters more profitable investment opportunities (a lower η) and has stronger incentives to cash out by selling loans to investors through OTD. At the same time, during boom periods, housing prices are also expected to be relatively high (high μ_P), and the costs of negotiation on defaulted loans are likely to be low (easier to sell, thus a higher γ). All of these increase the bank's incentive to securitize loans, consistent with findings in Chernenko et al. (2014). In contrast to Chernenko et al. (2014), I show that pro-cyclicality holds even without differences in beliefs between the bank and investors.

1.5.3 Securitization and Subprime Mortgage Lending

As many studies argue, securitization led to expanded lending by linking investors with loan applicants, especially during the private label securitization boom starting in the early 2000s (Mian and Sufi, 2009; Shin, 2009; Demyanyk and Van Hemert, 2011). During the same period, the economy also experienced rapid housing price growth. This is consistent with my model's prediction that securitization markets boost subprime lending only when housing price expectations are high enough. In this case, investors value mortgages more than the bank does. Selling loans through securitization is preferable for banks and thus they extend subprime mortgage lending. Access to securitization markets alone is not, however, sufficient for subprime mortgage credit expansion. Keys et al. (2012a) show that the securitization market existed for a long time, but had never before caused the troubles seen in the subprime mortgage crisis of 2007-09.

1.5.4 Defaults and Foreclosure

Given ex ante aggressive subprime mortgage credit expansions, the model predicts that when housing prices decline, more ex post mortgage defaults are expected if housing price expectations were higher and if banks were exposed more to securitization markets. Demyanyk and Van Hemert (2011) and Rajan et al. (2015) find that securitized loans had higher default rates than the unsecuritized loans issued in 2001-2006. Housing price declines lead to more defaults. At the same time, the inefficient renegotiation of securitiers results in more foreclosures, which further exaggerated housing price declines. Foote et al. (2012) find that massive defaults were followed by a sharp housing price decline starting in 2007.

1.5.5 Heterogeneities across Housing Price Expectations and Exposures to Securitization Markets

Both the theoretical and the empirical literature point to high housing price expectations and the securitization boom, which co-existed prior to the recent subprime mortgage crisis. However, as mentioned in Section 1, to my knowledge, no previous studies have taken the interaction effect between these two factors into account. According to the theoretical framework I established in the sections above, there are substantial heterogeneous effects from high housing price expectations and exposure to securitization markets, which reinforce each other's impact on subprime lending. The testable empirical implications from my model are twofold: (1) markets with higher housing price expectations and greater exposure to securitization are characterized by higher subprime mortgage credit; and (2) markets with larger subprime mortgage expansion suffer more defaults. These two main hypotheses are tested in the following empirical analysis.

1.6 Empirical Analysis

In this section, I use data to empirically test two main hypotheses obtained from the theoretical predictions.

- *H1: Banks with higher OTD exposure operating in markets with higher housing price expectations extend loan to riskier borrowers.*
- *H2: Banks with higher OTD exposure operating in markets with higher housing price expectations have higher default rates.*

To conduct these tests, I extend the identification strategy in Purnanandam (2011) by incorporating housing price variations across markets.[28]

1.6.1 Data

The main source of the data used in this paper is the call report database for bank information. All Federal Deposit Insurance Corporation (FDIC)-insured commercial banks are required to file quarterly call reports with the regulators The reports contain detailed information on the bank's income statement, balance-sheet items, and off-balance-sheet activities. Beginning with the third quarter of 2006, banks started to report information regarding their mortgage activities, especially 1) the origination of 1-4 family residential mortgages during the quarter with the purpose of reselling in the market; and 2) the extent of 1-4 family residential mortgages that were actually sold during the quarter, allowing me to measure banks' participation in the OTD market. The key measure of OTD activity is the ratio of loans originated for resale during the quarter, scaled by beginning-of-the-quarter mortgage loans of the bank, which captures the level of bank participation in the OTD market.[29]

As a supplement to these data, the HDMA (Home Mortgage Disclosure Act) database for loan details is used to identify the primary market of each bank, where the bank has the

[28]To guarantee my analysis align with Purnanandam (2011), I firstly replicate his benchmark results presented in Table A.1 to Table A.3 in Appendix A.2. Though my sample size is slightly smaller than that in his original paper, all main results are replicable with very close magnitude.

[29]As defined in Purnanandam (2011).

largest fraction of its mortgage loans. Other supplemental data on quarterly updated housing price indices across MSAs and Zip-based regions are from the Federal Housing Finance Agency (FHFA). By linking housing price indices to banks' primary markets, I construct housing price growth and decline in each market to capture housing price variations across different markets.

In my analyses, I focus on all banks with available data on mortgage origination for resale from 2006Q3 to 2008Q1.[30] Then, I create a balanced-panel of banks in the database for seven consecutive quarters by matching banks covered in the HMDA database in 2006.[31]

Table 3.1 provides the summary statistics of key variables used in this paper. To reduce effects of outliers, all continuous variables are winsorized at 1% from both tails. The average bank size is about \$5.5 billion, with a mortgage to total assets ratio of around 0.17. The chargeoffs and fraction of non-performing mortgages to total mortgages are used to measure mortgage defaults, with an average of 0.09 percent and 2.03 percent, respectively. The average OTD mortgage to total mortgage ratio is 0.24 and the average last-3-year housing price growth is 24 percent. Figure 1.6 plots the relationship between otd and $hgrowth3$. As discussed in Proposition I.2, the profit differential from OTD against from OTH is increasing in housing price expectations. Thus it is expected that in markets with faster housing price growth, banks' OTD participations are higher. This is confirmed by Figure 1.7, in which the slope for banks in markets with housing price growth above the mean is steeper than the slope for banks in markets with housing price growth below the mean. In other words, it is consistent with another model prediction that higher housing price expectations enhance the attractiveness of securitization markets. In the next two sections, I conduct empirical tests on the two hypotheses proposed above.

[30] An unexpected securitization market shutdown in 2007 will be used as the basis for identification, as in Purnanandam (2011). To deal with the confounding effect from giant banks, I also conduct robustness checks by excluding banks with total assets more than \$10 billion.

[31] As pointed out in Purnanandam (2011), this balanced panel filter is used to exploit the variation in mortgage default rates of the same bank over time, as the mortgage market passed through the period of stress. For robustness, though not reported here, removing this filter does not alter the results.

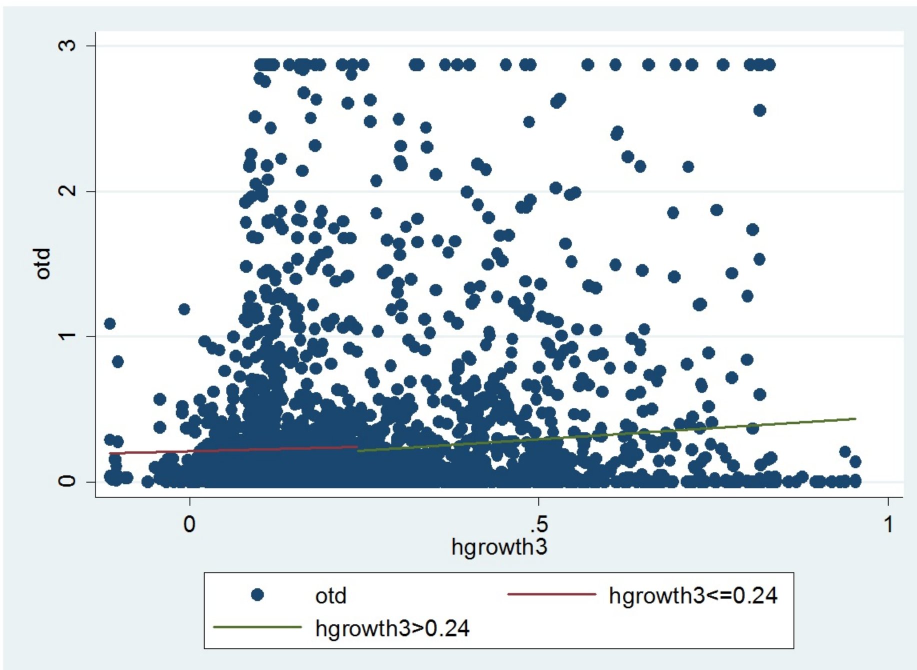
Table 1.1: Variable Definitions and Summary Statistics

Variable	Definition	Obs	Mean	Std. Dev.	P25	P75	Min	Max
ta	Total assets in billion dollars	4445	5.51	20.79	0.42	2.15	0.05	166.03
mortgage_ta	The ratio of mortgage to total assets	4445	0.17	0.10	0.10	0.22	0.01	0.51
cil/ta	The ratio commercial and industrial loans to total assets	4445	0.11	0.07	0.06	0.14	0.00	0.35
chargeoff	The chargeoff on mortgage portfolio as a percentage of mortgage assets	4442	0.09	0.19	0.00	0.09	0.00	1.28
npa/ta	The ratio of non-performing assets to total assets (%)	4445	0.34	0.46	0.08	0.41	0.00	2.82
mortgnpa	The ratio of non-performing mortgages to total mortgages (%)	4442	2.03	2.36	0.63	2.45	0.00	14.45
tier1cap	The ratio of tier-one-capital to risk-adjusted assets (%)	4057	11.51	3.52	9.60	12.16	8.03	36.24
liquid	The bank's liquid assets to total assets ratio	4057	0.09	0.07	0.04	0.12	0.01	0.44
absgap	The absolute value of one-year maturity gap as a fraction of total assets (%)	4445	0.14	0.11	0.05	0.20	0.00	0.52
otd	Mortgages originated with a purpose to sell as a fraction of total mortgages	3682	0.24	0.49	0.00	0.22	0.00	2.87
hgrowth3	The housing price growth in the last three years	4382	0.24	0.18	0.12	0.31	-0.11	0.95
preotd	The three-quarter average otd from 2006Q3 to 2007Q1	635	0.24	0.55	0.00	0.20	0.00	5.49
prehgrowth3	The three-quarter average hgrowth3 from 2006Q3 to 2007Q1	635	0.28	0.21	0.13	0.39	0.00	0.91

This table provides the summary statistics of key variables used in the study. All continuous variables are winsored at 1%

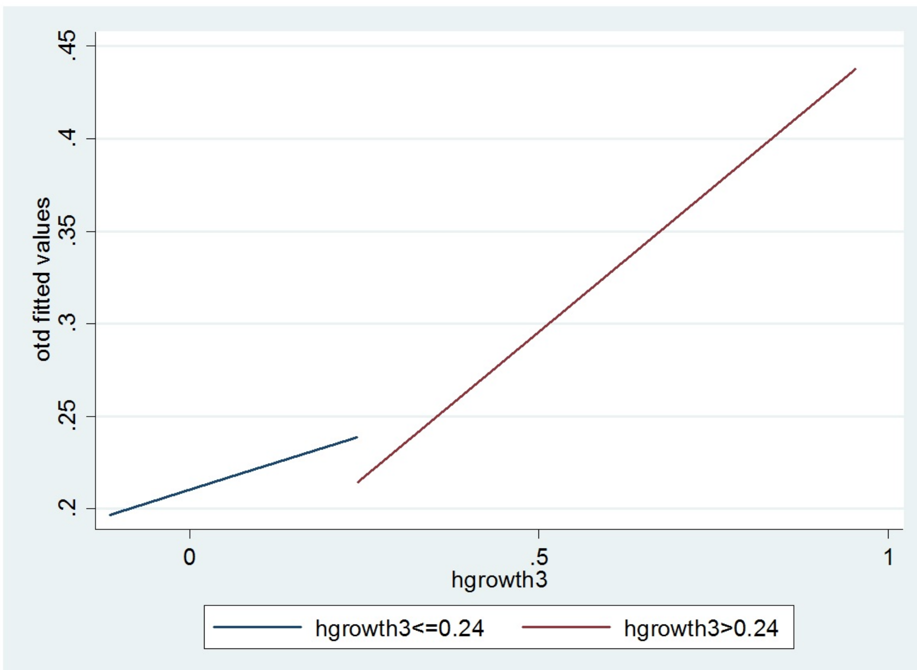
This table provides the summary statistics of key variables used in the study. All continuous variables are winsored at 1% Absolute value of t-statistics in brackets.

Figure 1.6: Scatter Plots between OTD and House Price Growth in the Past 3 Years



Notes: This graph is a scatter plot between *otd* and *hgrowth*3. The blue fitted line is for those whose housing price growth is below the mean (0.24) and the red fitted line is for those whose housing price growth is above the mean.

Figure 1.7: Fitted Lines of OTD on House Price Growth in the Past 3 Years



Notes: This graph includes two fitted lines of *otd* on *hgrowth*3. The blue fitted line is for those whose housing price growth is below the mean (0.24) and the red fitted line is for those whose housing price growth is above the mean.

1.6.2 Ex Ante Mortgage Credit Expansion

The hypothesis on ex ante mortgage credit expansion states that, compared to other banks, banks with high OTD market participation operating in markets with high housing expectations offer loans more aggressively. To test this hypothesis, information on housing price expectations are essential. However, existing databases that include such information are very limited, especially those with local market variations.[32]

In this paper, I will try to use two different proxies for housing price expectations. First, I would make a rational expectation assumption by assuming that the ex post realized house price is a good proxy for the ex ante housing price expectation. This strategy is often used in estimating stock returns under the rational expectations model. One key restriction here is that there should not be any realized unexpected shocks that are correlated to the ex post realized house price. Therefore, I first use the market level next 1-year house price growth as a proxy for the current housing price expectation for each market for any given period. Since it is a realized outcome, the endogeneity issue regarding housing price expectations is mitigated.

Therefore, I only use cross-sectional analysis on samples of year 2006 (pre-crisis) and year 2008 (post-crisis), respectively.[33] An important caveat to be pointed out: even after removing samples in year 2007, where an unexpected shock occurred, using realized house prices as proxies for housing price expectations helps mitigate the endogeneity issue, but still suffers from the measurement error problem. This measurement error issue, also known as "Errors-in-Variables", leads to attenuation bias and makes the estimated coefficients to be inconsistent and biased toward zero. Due to data limitation, the adjustment I adopted here can only alleviate but cannot completely overcome this problem. However, I would argue

[32] For example, Pulsenomics conducted a Home Price Expectation Survey by interviewing over 100 economists, investment strategists, and housing market analysts regarding five-year expectations for future home price in the U.S. for every quarter, but it concerns the U.S. market as a whole.

[33] As an indirect evidence that year 2007 sample is affected by the sudden crisis and that the rational expectation assumption may not be plausible for 2007, the results reported in A.4 show that most of results except for approval rate are insignificant.

that, the estimated coefficients, if any, are non-zero, then the estimation strategy used here can, at minimum, provide a lower bound of estimated coefficients.

The estimation equation is as follows:

$$riskiness_i = \mu_i + \beta_1 otd_i + \beta_2 hgrowth3_j + \beta_3 otd_i * fhgrowth_j + \sum_{k=1}^{K} \beta X_i + \epsilon_{ij} \tag{1.31}$$

where the dependent variable, $riskiness$, measures bank i's loan riskiness at the beginning of quarter t. otd is the bank's fraction of originated-to-sell mortgage loans , scaled by its total mortgage loans. $fhgrowth$ denotes the house price growth in the next 1 year on market j, which serves as a proxy for housing price expectations. The main variable of interest is the interaction term of these two variables: $otd * fhgrowth$. I expect that banks with high OTD and with major business in markets with high house prices (thus high housing expectations) extend their loans to riskier borrowers than other banks. To match the quarterly bank level data from Call Report with the annual loan level data from HMDA. I mainly use the last quarter of previous years as a benchmark.

I conduct the analysis at loan level. In terms of riskiness measures, I mainly use three measures from HMDA data when linking loans to their originating banks: 1) whether a loan application is approved; if approved 2) the loan-to-income ratio; and 3) the interest spread of the loan.[34] The results are presented in Table 1.2. As we can see from the table, the coefficients on the interaction term of securitization rate (otd) and future house price growth (fhgrowth) are all positive and statistically significant. It is shown that, in markets with faster house price growth, banks with more securitized loans 1) approve applications more easily, 2) grant loans with larger loan-to-income ratio, and 3) grant loans with larger interest spreads. In other words, all these results confirm the hypothesis regarding the ex ante risky lending.

Secondly, in order to capture the whole sampling period and investigate the effect of

[34] Another possible measure of riskiness is the FICO score for each loan applicant. Due to data limitation, it is not included in HMDA data.

Table 1.2: Future Housing Price Growth and OTD on Ex Ante Loan Risk

	Year 2006 (Prior to Crisis)			Year 2008 (Post Crisis)		
	Approval	LTI	Spread	Approval	LTI	Spread
fhgrowth	0.024***	-0.160***	0.023	0.047***	-0.355***	0.131***
	[17.96]	[16.24]	[1.35]	[47.65]	[58.57]	[11.39]
otd	-0.094***	0.126***	-0.841***	-0.040***	0.224***	-0.704***
	[36.53]	[6.29]	[3.24]	[12.02]	[11.41]	[15.19]
otd*fhgrowth	0.018***	0.035***	0.103***	0.018***	0.046***	0.182***
	[11.66]	[3.19]	[5.59]	[10.40]	[4.60]	[8.54]
logta	-0.034***	-0.16***	0.023*	-0.054***	-0.021***	-0.215***
	[56.01]	[22.30]	[1.64]	[68.20]	[4.54]	[23.75]
cil/ta	-1.526***	-0.154*	0.692***	-1.292***	-0.841***	0.475***
	[160.36]	[1.95]	[6.15]	[150.22]	[14.19]	[4.53]
liquid	0.282***	-0.648***	-0.356	-0.457***	-1.923***	0.472***
	[16.84]	[5.71]	[1.49]	[37.78]	[26.59]	[3.30]
absgap	-0.047***	0.954***	0.775***	0.007	0.617***	0.287***
	[4.70]	[14.16]	[5.42]	[0.90]	[13.01]	[2.66]
Observations	199308	15332	23054	349919	266542	33808
R-squared	0.18	0.04	0.03	0.14	0.03	0.03

This table provides the regression results of future housing price growth and bank's OTD on average riskiness for bank loans using a bank fixed effects model conducted at loan level. The dependent variables are 1) approval indicator; 2) loan-to-income ratio; and 3) interest spread. otd is the ratio of OTD mortgages to total mortgages. fhgrowth is the house price growth in the next year in the bank's primary market. loan amount is the amount of loan granted; logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of one-year maturity gap as a fraction of total assets; year 2008 is a year dummy variable. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

housing price expectations together with securitization, I assume, instead, that housing price expectations are formed adaptively–i.e., people use the past house price growth in the market as an indicator for the pattern of the house price in the future.[35] Thus, I use these riskiness measures as dependent variables and estimate on it the effects of high-OTD together with high housing price expectations. The estimation equation is as follows:

$$riskiness_{it} = \mu_i + \beta_1 otd_{it} + \beta_2 hgrowth3_{jt} + \beta_3 otd_{it} * hgrowth3_{jt} + \sum_{k=1}^{K} \beta X_{it} + \epsilon_{ijt} \quad (1.32)$$

where the dependent variable, *riskiness*, measures bank i's loan riskiness at the beginning of quarter t. *otd* is the bank's fraction of originated-to-sell mortgage loans in quarter t, scaled by its total mortgage loans. $hgrowth3$ denotes the house price growth in the past 3 years on market j at quarter t, which serves as a proxy for housing price expectations. The main variable of interest is the interaction term of these two variables: $otd * hgrowth3$. I expect that banks with high OTD and with major business in markets with high house prices (thus high housing expectations) extend their loans to riskier borrowers than other banks. To match the quarterly bank level data from Call Report with the annual loan level data from HMDA. I mainly use the last quarter of previous years as a benchmark. To be specific, I use two-year HMDA data, 2007 and 2008, and match the call report data from the 4th quarter of 2006 and 2007, respectively to them. The idea is to use the historical house price growth up to the last quarter of the previous year as proxy for house price expectations for the following year to capture the ex ante lending decisions. [36]

I conduct this test at two levels. I first run a bank level analysis by using the average riskiness measures for each bank. Secondly, to further control for potential heterogeneous effects stemmed from loan characteristics, I also conduct a test at loan level. Respective results are presented in Table 1.3 and Table 1.4. As we can see from these two tables,

[35] This is just an adaptive belief assumption, which may involve more endogeneity concerns that past house price growth may be affected by securitization activities. However, as a robustness check, using this different proxy for future housing price expectations will justify findings as shown before.

[36] For robustness, I also use the first quarter of each year's call report data to match with HMDA. Though not reported here, the results are qualitatively similar.

Table 1.3: Housing Price Growth and OTD on Ex Ante Loan Risk (Bank Level Analysis)

	Average Approval	Average LTI	Average Spread
otd	-0.051	-0.063	0.325
	[1.55]	[0.31]	[1.33]
hgrowth	-0.003	-0.047	0.045
	[0.47]	[1.02]	[0.87]
otd*hgrowth	0.030**	0.102	0.199**
	[2.35]	[1.27]	[2.12]
avg loan amount	0	0.002***	-0.001
	[0.22]	[4.08]	[1.07]
logta	0	0.427	-0.06
	[0.00]	[1.57]	[0.20]
cil/ta	0.132	-1.376	0.443
	[0.43]	[0.70]	[0.20]
liquid	0.335	-0.08	-0.279
	[1.55]	[0.06]	[0.18]
absgap	-0.244***	0.342	0.981
	[2.72]	[0.60]	[1.54]
year 2008	-0.028***	-0.145***	0.127**
	[3.42]	[2.84]	[2.25]
Observations	823	823	738
R-squared	0.89	0.84	0.84
Bank fixed-effects	Yes	Yes	Yes

This table provides the regression results of past housing price growth and bank's OTD on average riskiness for bank loans using a bank fixed effects model. The dependent variables are 1) average approval rate; 2) average loan-to-income ratio; and 3) average interest spreads. otd is the ratio of OTD mortgages to total mortgages. hgrowth3 is the house price growth in the last three years in the bank's primary market. avg loan amount is the average amount of mortgages granted; logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of one-year maturity gap as a fraction of total assets; year 2008 is a year indicator. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

Table 1.4: Housing Price Growth and OTD on Ex Ante Loan Risk (Loan Level Analysis)

	Approval	LTI	Spread
otd	-0.041***	-0.108***	0.606***
	[6.61]	[2.90]	[8.15]
hgrowth	-0.001	-0.003	0.490***
	[0.44]	[0.25]	[5.18]
otd*hgrowth	0.019***	0.026***	0.082**
	[16.70]	[3.34]	[2.29]
loan amount	0.024***	0.775***	-0.703***
	[44.54]	[221.28]	[124.55]
logta	0.037***	0.131**	0.024
	[4.26]	[2.51]	[0.26]
cil/ta	0.230***	0.33	-1.123
	[3.41]	[0.82]	[1.31]
absgap	-0.065***	0.204*	-1.801***
	[3.45]	[1.75]	[7.75]
year 2008	-0.040***	-0.118***	0.024
	[25.62]	[12.36]	[1.27]
Observations	593709	444723	61417
R-squared	0.24	0.16	0.35
Bank fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
MSA fixed-effects	Yes	Yes	Yes

This table provides the regression results of past housing price growth and bank's OTD on average riskiness for bank loans using a bank fixed effects model conducted at loan level. The dependent variables are 1) approval indicator; 2) loan-to-income ratio; and 3) interest spread. otd is the ratio of OTD mortgages to total mortgages. hgrowth3 is the house price growth in the last three years in the bank's primary market. loan amount is the amount of loan granted; logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of one-year maturity gap as a fraction of total assets; year 2008 is a year dummy variable. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

the coefficients on the interaction term of securitization rate (otd) and house price growth (hgrowth3) are all positive and statistically significant, except for the specification with loan-to-income ratio in the bank level analysis. It is shown that, in markets with faster house price growth, banks with more securitized loans 1) approve applications more easily, 2) grant loans with larger loan-to-income ratio, and 3) grant loans with larger interest spreads. In other words, all these results confirm the hypothesis regarding the ex ante risky lending.

As additional supporting evidence, we know that each bank's loan origination for any given period is another possible key variable to measure the extent of banks' credit expansion, especially for originations of subprime and other low-quality mortgages. However, call report data do not provide detailed information on total loan originations. I use the ratio of actual sales scaled by total mortgages at the beginning of each quarter to indirectly test the hypothesis. Specifically, from the model's prediction, the ex ante subprime mortgage expansion comes from the fact that these loans can be sold to investors through securitization markets. Therefore, the more that a bank can sell, the more incentives a bank has to originate new mortgage loans. A strong positive correlation between loan origination and loan sales is expected. Thus, these banks also sell larger fraction of mortgages in the OTD markets.

Before the main specification, pre-tests in Model 1 and Model 2 in Table 1.5 confirm that both OTD participation and high housing prices are positively correlated to mortgage sales. Further, as shown in Model 3 in Table 1.5, I find a positive and statistically significant coefficient of 0.007 on the interaction term of OTD and the current house price, indicating that high-OTD banks in markets with high house prices (thus high house price expectations) sell more mortgages in OTD markets. In particular, conditional on the mean of otd (i.e., 0.24), when the house price growth increases from the 25 percentile (i.e., 0.12) to the 75 percentile (i.e., 0.31), the ratio of mortgage sales to total mortgages increases by 0.018. Meanwhile, conditional on the mean of $hgrowth3$ (i.e., 0.24), when otd increases from the 25 percentile (i.e., 0) to the 75 percentile (i.e., 0.22), the ratio of mortgage sales to total mortgages increases by 0.013. The result persists when excluding large banks, as shown in

Table 1.5: Housing Price and OTD on Ex Ante Loan Sale

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
otd	0.182***		-0.113***	-0.119***	-0.059*	-0.063*
	[8.34]		[3.76]	[4.03]	[1.77]	[1.92]
hgrowth3		0.163***	-0.077	-0.061	-0.081	-0.066
		[3.77]	[1.60]	[1.24]	[1.55]	[1.26]
otd*hgrowth3			0.720***	0.759***	0.658***	0.691***
			[12.57]	[13.29]	[10.53]	[11.10]
after					-0.02	-0.018
					[1.40]	[1.27]
after*otd					0.013	0.008
					[0.47]	[0.30]
after*hgrowth3					0.132***	0.114**
					[2.74]	[2.34]
after*otd*hgrowth3					-0.368***	-0.356***
					[4.37]	[4.26]
logta	-0.021	0.002	0.01	0.032	0.035	0.063
	[0.49]	[0.06]	[0.25]	[0.82]	[0.84]	[1.50]
cil_ta	-0.442	-0.402	-0.097	-0.175	-0.02	-0.096
	[1.30]	[1.54]	[0.32]	[0.57]	[0.07]	[0.32]
liquid	0.874***	0.606***	0.814***	0.442**	0.780***	0.397**
	[4.55]	[3.86]	[4.71]	[2.47]	[4.49]	[2.21]
absgap	0.300***	0.159**	0.107	0.029	0.102	0.023
	[2.98]	[2.02]	[1.21]	[0.32]	[1.17]	[0.27]
Observations	3304	3999	3248	3159	3248	3159
R-squared	0.97	0.97	0.98	0.98	0.98	0.98
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

This table provides the regression results past housing price growth and bank's OTD on ex post defaults using a bank fixed effects model. The dependent variable, sold, measures bank i's mortgage sale as a fraction of its total mortgage loans at the beginning of quarter t. after is a dummy variable that equals to zero for quarters before and including 2007Q1. otd is value of OTD mortgages to total mortgages. hgrowth3 is the house price growth during the last three years in the bank's primary market. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of one-year maturity gap as a fraction of total assets. All continuous variables are winsored at 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

Model 4. In Model 5 and Model 6, I further show that this expansion effect is constrained after closure of the subprime mortgage market, where the coefficient on the triple interaction term $after * otd * hprice$ is negative and statistically significant. It indicates that after the securitization market closure, the mortgage sale reduces across markets.

1.6.3 Ex Post Defaults

In this section, I test the second hypothesis regarding ex post defaults. There is one major data challenge for this test: once mortgages are securitized, they will pool together with many other mortgages originated from different banks and thus the actual defaults cannot be traced back and linked to the banks that originated them. In other words, the total defaults for each bank cannot be precisely measured. To overcome this data issue, I take the unexpected secondary mortgage market closure in the middle of 2007 as the main exogenous variation. The key idea is as follows: before this market closure, each bank could choose whatever amount it wants to securitize. Once the market froze, banks stuck with loans that they had intention to sell when they originated them but could not easily sell them anymore and had to retain them on their balance sheets. Therefore, the actual default rate of all mortgages that a bank originated can be precisely measured right after the market closure.

However, the loans meant to be sold were low-quality ones that were not carefully screened by high-OTD banks. Along with this mechanism, Purnanandam (2011) finds that high-OTD banks in quarters immediately following the onset of the crisis had higher mortgage default rates than low-OTD banks that originated most of their loans with the intention of keeping them on the balance sheets. I extend this empirical design by incorporating housing price variations across local markets. First, I use HMDA loan data to identify each bank's primary market at the three-digit zip code level. The bank's primary market is defined as the region with the largest fraction of the bank's mortgages. Since the default analysis involves data ranging from prior to the ciris to the post-crisis samples, where the shock of sudden market closure lies in tween, the rational expectation assumption may not be applicable in this exercise. Thus, alternatively, I will simply follow the adaptive belief assumption used in the previous section. In particular, for each market, I construct the last three-year housing price growth prior to 2007Q1, the onset of the secondary mortgage market closure. I expect that banks with high-OTD and running business mainly in markets with fast housing price growth would extend mortgages aggressively to riskier borrowers. After the market closure, their defaults would be the greatest.

I adopt a difference-in-difference-in-differences (DDD) estimation strategy by focusing on the triple interaction term of OTD exposure prior to market closure, housing price growth prior to market closure and a time indicator for market closure. The estimation equation is as follows:

$$
\begin{aligned}
default_{it} = \mu_i + \beta_1 after_t + \beta_2 after_t * preotd_i + \beta_3 after_t * prehgrowth3_j + \beta_4 after_t * premortgage_i \\
+ \beta_5 after_t * preotd_i * prehgrowth3_j + \beta_6 after_t * premortgage_i * prehgrowth3_j \\
+ \sum_{k=1}^{K} \beta X_{it} + \epsilon_{ijt} \qquad (1.33)
\end{aligned}
$$

The dependent variable of this model measures the default rate of the mortgage portfolio of bank i in quarter t. I use net-chargeoffs and non-performing mortgages as two measures of default.[37] μ_i is the bank fixed effects, and X_{it} is a vector of bank characteristics. The coefficient β_5 on the triple interaction term is of key interest, as it measures the change in chargeoffs/NPAs around the crisis period across banks with varying intensities of OTD market participation and varying market housing price growth. Corresponding interactions with *premortgage* are included to ensure that the effect is not simply an artifact of higher involvement in mortgage lending by higher-OTD banks. A host of bank characteristics that can potentially affect the quality of mortgage loans are included as controls.[38]

Table 1.6 presents the estimation results. Results in Model 1 and Model 2 are based upon

[37]Both variables are scaled by the bank's total mortgage loans measured as of the beginning of the quarter.
[38]Please refer to Purnanandam (2011) for detailed discussions.

Table 1.6: Housing Price Growth and OTD on Mortgages Defaults

	Model 1 Chargeoffs	Model 2 NPA	Model 3 Chargeoffs	Model 4 NPA
after	0.007	0.218	0.011	0.062
	[0.40]	[1.40]	[0.62]	[0.39]
after*preotd	-0.040**	0.174	-0.040**	0.211
	[2.08]	[1.00]	[2.09]	[1.22]
after*premortgage	0.074	0.597	0.05	1.402*
	[0.89]	[0.78]	[0.58]	[1.82]
after*prehgrowth3	0.087**	0.39	0.078*	0.906**
	[2.02]	[0.98]	[1.76]	[2.26]
after*preotd*prehhgrowth3	0.269***	1.132***	0.273***	0.911**
	[6.46]	[2.97]	[6.46]	[2.40]
after*premortgage*prehhgrowth3	-0.379	-0.186	-0.298	-4.254**
	[1.63]	[0.09]	[1.24]	[1.97]
logta	0.053**	0.725***	0.046*	1.044***
	[2.03]	[3.07]	[1.72]	[4.39]
cil/ta	-0.146	0.048	-0.147	0.024
	[0.75]	[0.03]	[0.75]	[0.01]
liquid	0.237**	1.948*	0.277**	-0.02
	[2.01]	[1.81]	[2.26]	[0.02]
absgap	-0.088	-2.513***	-0.094	-2.695***
	[1.49]	[4.65]	[1.56]	[4.95]
Observations	4056	4056	3958	3958
R-squared	0.47	0.7	0.47	0.71
Bank fixed-effects	Yes	Yes	Yes	Yes

This table provides the regression results on past housing price growth and bank's OTD on ex post defaults using a bank fixed effects model. The dependent variable, default, is measured by either the mortgage chargeoffs or non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. after is a dummy variable that equals zero for quarters before and including 2007Q1. preotd is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. prehgrowth3 measures the bank's primary market's housing price growth in the three years before 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of a one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

all observations that pass the sample refinements as described in the Data section. Model 3 and Model 4 exclude large banks with an asset size of more than $10 billion to avoid the possible contamination effect from large banks that run business in multiple markets. I find that high participation in the OTD market, together with high housing price growth during the pre-disruption period, had a significant effect on a bank's mortgage default rates during the post-disruption quarters. In Model 1, I find a positive and significant coefficient of 0.269 on $after*preotd*prehgrowth3$, which represents a 0.040 percent increase in a bank's chargeoff after the closure of the securitization market. Moreover, conditional on the mean of *preotd* (which is 0.24), when the housing price growth before market closure ($prehgrowth3$) increases from the 25 percentile (which equals 0.13) to the 75 percentile (which equals 0.39), the bank's chargeoff increases by 0.039 percent. On the other hand, conditional on the mean of $prehgrowth3$ (which is 0.28), when *preotd* increases from the 25 percentile (i.e., 0) to the 75 percentile (i.e., 0.2), the bank's chargeoff increases by 0.007 percent. In Model 2, I also find a positive and significant effect of this interaction term on non-performing mortgages, which equals a 0.36 percent increase in non-performing loans after the closure of the securitization market. Conditional on the mean of *preotd*, when the housing price growth before market closure ($prehgrowth3$) increases from the 25 percentile to the 75 percentile, the bank's non-performing loans increases by 0.18 percent. Conditional on the mean of $prehgrowth3$, when *preotd* increases from the 25 percentile to the 75 percentile, the bank's non-performing loans increases by 0.03 percent. When large banks are excluded, results in Models 3 and 4 are similar.

To analyze the effect of loans that a bank originated to distribute but was unable to distribute due to the secondary mortgage market closure, I also use *stuck*, a refined measure of *preotd* to re-estimate the $default$ regression, by replacing *preotd* with *stuck*.[39] Table 1.7 reports the re-estimation results. Across the four different specifications, I find qualitatively the same results as those in Table 1.6.

[39]Purnanandam (2011) presents the detailed definition of variable *stuck* on P1895.

Table 1.7: Housing Price Growth and Inability to Sell on Mortgage Defaults

	Model 1	Model 2	Model 3	Model 4
	Chargeoffs	NPA	Chargeoffs	NPA
after	0.005	0.256	0.01	0.083
	[0.28]	[1.62]	[0.57]	[0.51]
after*stuck	0.009	-0.031	0.006	0.144
	[0.35]	[0.13]	[0.22]	[0.60]
after*premortgage	0.031	1.031	0.001	1.835**
	[0.37]	[1.31]	[0.02]	[2.30]
after*prehgrowth3	0.064	0.099	0.052	0.661*
	[1.54]	[0.26]	[1.21]	[1.69]
after*stuck*prehgrowth3	0.179***	2.350***	0.195***	1.591***
	[3.10]	[4.41]	[3.31]	[2.97]
after*premortgage*prehgrowth3	-0.138	-0.828	-0.046	-4.711**
	[0.60]	[0.39]	[0.19]	[2.19]
logta	0.064**	0.636***	0.055**	0.965***
	[2.44]	[2.63]	[2.06]	[3.95]
cil/ta	-0.297	-0.574	-0.306	-0.375
	[1.52]	[0.32]	[1.54]	[0.21]
liquid	0.212*	1.978*	0.260**	0.021
	[1.85]	[1.87]	[2.17]	[0.02]
absgap	-0.032	-2.082***	-0.037	-2.301***
	[0.55]	[3.85]	[0.62]	[4.22]
Observations	3740	3740	3642	3642
R-squared	0.47	0.71	0.47	0.72
Bank fixed-effects	Yes	Yes	Yes	Yes

This table provides the regression results on past housing price growth and bank's inability to sell loans through OTD on ex post defaults using a bank fixed effects model. The dependent variable, default, is measured by either the mortgage chargeoffs or non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. after is a dummy variable that equals zero for quarters before and including 2007Q1. stuck measures the difference between loans originated before 2007Q1 and loans sold after this quarter. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. prehgrowth3 measures the bank's primary market's housing price growth in the three years before 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of the one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

The identification strategy above uses mainly an exogenous shock on the OTD market that could alter ex post defaults by restricting high-OTD banks to retaining origination-for-sales mortgages. As another side of the model prediction, a realization of low housing price will also lead to more ex post defaults. To test this possibility, I replace the time indicator for subprime mortgage market closure $after$ with the current house price decline *decline*, defined as the drop of the house price from the last quarter to the current quarter. This is a more direct way to capture the effect caused by the decline in housing prices. However, the price decline may be anticipated by borrowers and even by banks. Thus, they may adjust their default and selling decisions accordingly, which will raise some identification challenges. Therefore, I present these results with caution as they establish only the correlations and not the causal effects. As shown in Table 1.8, I find some evidence that high-OTD banks in markets with high housing price growth have high defaults when the realized house price declines. In particular, the effect of the interaction term $preotd * prehgrowth3 * decline$ on mortgage chargeoffs is positive and statistically significant in both Model 1 and Model 3.

1.6.4 Discussion

The empirical results from the previous two sections must be interpreted with some cautions. First, in my model, I do not allow the possibility of forced default, in which borrowers do not have enough money to make the mortgage payment. However, these borrowers often have low credit and low income, as well as lower default costs. Consequently, they are more likely to default either compulsorily or voluntarily (strategically). Therefore, our empirical results can still be interpreted as follows: high-OTD banks in markets with high housing price growth have relatively poor mortgage pools and, thus, suffer defaults more ex post.

The other important issue is with respect to the empirical design of testing the hypothesis about ex ante mortgage expansions. As mentioned before, direct and reliable data on regional-market housing price expectations and banks' mortgage originations are desirable.

Table 1.8: Realized House Price Decline on Mortgages Defaults

	Model 1 Chargeoffs	Model 2 NPA	Model 3 Chargeoffs	Model 4 NPA
decline	-0.802	-14.446**	-0.641	-16.176**
	[1.03]	[2.07]	[0.80]	[2.29]
preotd*decline	0.528	20.544**	0.476	19.962**
	[0.53]	[2.28]	[0.47]	[2.22]
premortgage*decline	2.018	18.078	1.091	39.78
	[0.52]	[0.52]	[0.27]	[1.12]
prehgrowth3*decline	2.925**	35.390***	2.604*	45.274***
	[2.16]	[2.91]	[1.88]	[3.68]
preotd*prehgrowth3*decline	4.275***	3.561	4.397***	2.32
	[2.60]	[0.24]	[2.64]	[0.16]
premortgage*prehgrowth3*decline	-6.817	106.178	-4.153	-26.527
	[0.86]	[1.48]	[0.50]	[0.36]
logta	0.102***	1.521***	0.096***	1.722***
	[4.18]	[6.96]	[3.87]	[7.82]
cil/ta	-0.048	1.629	-0.055	1.527
	[0.24]	[0.91]	[0.27]	[0.85]
liquid	0.13	0.984	0.159	-1.064
	[1.09]	[0.92]	[1.28]	[0.97]
absgap	-0.109*	-2.638***	-0.114*	-2.668***
	[1.82]	[4.88]	[1.86]	[4.88]
Observations	4000	4000	3910	3910
R-squared	0.46	0.69	0.46	0.7
Bank fixed-effects	Yes	Yes	Yes	Yes

This table provides the regression results on past housing price growth and bank's OTD on ex post defaults using a bank fixed effects model. The dependent variable, default, is measured by either the mortgage chargeoffs or non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. decline measures the percentage housing price decline from the last quarter in the bank's primary market. preotd is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. prehgrowth3 measures the bank's primary market's housing price growth in the three years before 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of the one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

To further test that banks not only extend their lending but extend loans to even riskier borrowers, characteristics that measure the quality of each borrower are needed. In the current version, I match the bank level data from call reports to loan level data from HMDA to find out the relationship between housing price expectations and the decision to extend credit to lower quality borrowers. The riskiness of borrowers are measured by their approval rates, loan-to-income ratios, and risk spreads of granted mortgages. However, one limitation of HMDA data is that these risk measures are indirect measures that may not precisely capture borrowers' types. More direct measures, such as FICO scores, will substantially improve the tests, as in the data used in Brueckner et al. (2012) and Keys et al. (2010). In a future version, I plan to incorporate other data with FICO scores to further refine my test on the hypothesis about ex ante lending.

1.7 Conclusion

In this paper, I extend Brueckner (2000) and Brueckner et al. (2012) and build a simple contingent default model to explore the interaction between housing price expectations and the emergence of the originate-to-distribute (OTD) model through securitization. I show that high housing price expectations enhance the attractiveness of securitization markets for banks. When investors' renegotiation disadvantage is not severe, selling off loans to investors through OTD is always desirable for a bank. When investors' ability to renegotiate with borrowers is weak, a bank may prefer OTH to OTD, given that investors will demand to be compensated for anticipated default costs. Consistent with Brueckner et al. (2012), I show that increased housing price expectations strengthen the bank's incentives to extend credit to less creditworthy borrowers. Furthermore, I show that when housing price expectations are high enough, access to securitization markets magnifies the bank's incentives to engage in risky lending by extending loans to lower-quality borrowers. In addition, though my main results are derived under symmetric information, I further show that the presence of asymmetric information may only augment the results. Using data from call reports and from disclosures under the Home Mortgage Disclosure Act (HMDA), I provide evidence that supports my theoretical predictions. In particular, I find that banks doing more business in areas with higher housing price growth and originating more securitized mortgage loans are likely to lend to riskier borrowers, and thus suffer greater ex post defaults when house prices decline.

CHAPTER II

Credit Ratings with Economic Fluctuations: A Two-Sided Moral Hazard Approach

2.1 Introduction

Credit rating agencies (CRAs) are intended to screen and evaluate financial claims and assets issued in the market. As structured finance products became more prevalent during the past decade, credit rating agencies became more popular and expanded their business rapidly. However, in the recent 2008-09 financial crisis, credit rating agencies were blamed due to their lax ratings, that arguably were one major factor that contributed to this crisis (Frank, 2008). Therefore, understanding how the performance of credit rating varies across economic conditions is of great importance for policy makers to better regulate this market.

In this paper, we present a simple two-sided moral hazard model characterizing the interactions between an issuer and a credit rating agency (CRA). In our model, the originator (or the issuer) window dresses the financial claims it issues and seeks to get better ratings. The CRA cannot observe such window dressing efforts costlessly but chooses a screening effort to detect the issuer's window dressing, and investors in the market cannot observe the CRA's screening effort. Failure to detect window dressing incurs a reputation loss for the CRA. We highlight the fact that the CRA tends to screen and monitor less during economic booms, and, in turn, the issuer behaves countercyclically by window dressing more at the same time. This is consistent with recent empirical work on the market for structured finance products (Ashcraft et al., 2011; Griffin and Tang, 2012). Moreover, we show that, even when reputation loss is time-varying, as long as it is not too sensitive to economic conditions, the issuer still does more window dressing, and the CRA screens less when economic conditions improve.

Several studies have attempted to explain credit rating agencies' behavior over the business cycle. Bar-Isaac and Shapiro (2013) show that the time-varying reputation may induce countercyclical ratings quality. Bolton et al. (2012) also show that, with lower reputation costs, CRAs have greater incentives to inflate investment quality. Both papers focus solely on CRA rating concerns and ignore the possibility of issuers strategically adjusting their own strategies in anticipation. In contrast, we explicitly account for such interactions to show that the deterioration in credit quality is due partly to enhanced incentives to window dress in good times.

In addition, in an attempt to capture the dynamic evolution and interactions between the issuer and the credit rating agency, we use a psuedo-dynamic setting and show that when the issuer has an information advantage, she may or may not want to share her information with the CRA. The incentive to share information actually decreases when information about the state of the economy deteriorates.

This paper is closely related to two sets of studies. The first set theoretically characterizes issues in the credit rating industry. Among these issues, credit ratings shopping is prevalent. Sangiorgi and Spatt (2012) show that issuers can steal from investors through credit ratings shopping. Bolton et al. (2012) demonstrate that total welfare may also shrink due to credit ratings shopping. Benmelech and Dlugosz (2009) use data on ABS CDOs during the 2008-09 crisis and empirically confirm these theoretical predictions on ratings shopping. Opp et al. (2013) discuss another possible channel for ratings inflation. They show that when the regulatory advantage of highly rated securities is large enough, delegated information acquisition is unsustainable and will cause rating inflations. Meanwhile, Frenkel (2015) shows that inflated ratings could be a strategic tool for rating agencies to form a "double reputation" among both investors and issuers.

Another important feature of the credit rating market is reputation concerns, which can serve as a market discipline mechanism. Mathis et al. (2009) examine how reputation concerns affect the CRA's ratings quality and show that reputation alone is not enough for the CRA to always tell the truth. In addition, their dynamic model demonstrates that truth-telling incentives are weaker when the CRA has more business. In our model, our model requires that the CRA tell the truth, but the CRA may shirk from choosing its effort. We confirm that to properly discipline the CRA's screening choice, reputation loss should vary with changes in economic conditions.

To capture the interactions between issuers and CRAs, Cohn et al. (2013) study issuers' disclosure under pre-committed CRA screenings and show that when the CRA abandons screening completely, there are multiple equilibriums due to strategic complementarity. Manso (2013) also discusses possible feedback effects of credit ratings on issuers. In our model, we show that interactions between the issuer and the CRA is neither a strategic substitute nor a strategic complement and that this equilibrium without screening does not exist.

In terms of credit-rating market regulation, White (2010) states that having capital and investment requirements tied to ratings will enhance the importance and, thus, the market power of CRAs. Opp et al. (2013) show that introducing rating-contingent regulation that favors highly rated securities may increase or decrease rating informativeness, but unambiguously increases the volume of highly rated securities. Bongaerts et al. (2012) empirically test the role of multiple ratings and show that additional credit ratings exist for regulatory purposes and do not provide additional information related to credit quality.[1]

More broadly, this paper relates to second set of studies that explicitly or implicitly endow their models with the two-sided moral hazard feature. Among these, Bhattacharyya

[1]Boot et al. (2006) provide another rationale for credit rating agencies as a coordination mechanism whenever multiple equilibria exist.

and Lafontaine (1995) study the contractual arrangement involving revenue sharing. Povel et al. (2007) study equilibrium fraud and monitoring decisions and demonstrate that fraud peaks towards the end of a boom and is revealed in the ensuing bust. Khanna et al. (2008) investigate the IPO market during business cycles. They show that due to limited labor supply, investigation by the investment bank of each IPO application is low during booms, resulting in deeper underpricing. Costly state falsification models, which are used to study insurance and earnings manipulations, also share features of the two-sided moral hazard model (Crocker and Morgan, 1998; Crocker and Slemrod, 2007). Though these papers discuss different topics in different contexts, the simple two-sided moral hazard model, as a general and generic tool, can be applied to environments in which a player is monitored by an auditor sequentially, and the auditor is also an agent to another principal.

The paper is organized as follows. In Section 2, we present the model setup and timing. In Section 3, we analyze the main results regarding the first-best benchmark, the second-best equilibrium, and time-varying punishment. In Section 4, we discuss possible extensions and policy implications. Section 5 concludes.

2.2 Model Setup

I assume that there are three players in the market: an issuer, a credit rating agency (CRA), and competitive investors.[2] All players are risk-neutral. For the benchmark case, we assume the following timing scheme:

At the beginning of the game, the issuer is endowed with a financial claim that can be issued to the market. This financial claim can be either good (G) with intrisic value v_G with probability λ; or bad (B) with value v_B with probability $1-\lambda$, where $v_G > v_B$. For simplicity, we assume that both types of claims can be issued to the market i.e., both projects

[2] At this moment, to focus on the interaction effect between the issuer and the CRA, to avoid the potential complication from competition, we do not involve multiple players for these two groups. Later on, as extensions, we will discuss the multi-player case.

are positive NPV projects.[3] Nobody knows the exact quality of the financial claim, but the quality distribution is common knowledge. Before issuing the claim to the market, the issuer must turn to the CRA for a credit rating. Each claim generates a non-verifiable signal to be evaluated. When the claim is of the good type, it generates a good signal s^G, and when the claim is of the bad type, it generates a good signal with probability $p_w(q) = 1 - e^{-\frac{q}{1-\lambda}}$, which is a function of the issuer's window dressing effort q. Otherwise, it generates a bad signal s^B.This probability function is an increasing and concave function in q i.e., $p'_w(q) > 0$ and $p''_w(q) < 0$. The greater the effort q, the greater chance that the signal will be window dressed and the marginal increase is decreasing in q. Another feature of this probability function is that $p_w(0) = 0$ and $p_w(\infty) = 1$. When the issuer devotes zero effort, the signal will not be changed at all. When the issuer devotes an infinite amount of effort, the bad signal will become good with certainty.[4]

Since window dressing is costly, the issuer will devote a positive but finite amount of window dressing effort. Consequently, there is always positive probability that bad claims generate a good signal. The term $1 - \lambda$ captures the notion that successful window dressing depends on the expected quality of the claim. When the expected quality is higher (λ higher), the window dressing is relatively easier (i.e., given the same effort q, window dressing succeeds with greater probability for bad claims.). The marginal cost of window dressing is constant and equals a.

After the issuer's window dressing, the CRA will receive and evaluate the updated signal. The issuer pays a fixed fee f to the CRA for the evaluation.[5] I assume that, without evaluation, the financial claim cannot be issued.[6] Prior to observing the signal, the CRA

[3]In this setting, the existence of a CRA does not improve the efficiency through information production. Investors can simply invest in all claims at a price of pooled expected value. Again, this setting is only for illustrative purposes, and this simplified assumption should not undermine the importance of CRAs. For example, under an alternative setting in which the bad type claim is of negative NPV, the existence of a CRA will improve efficiency.

[4]Here, I assume that high-quality claims never "fail." This can be relaxed by introducing the possibility that both good claims and bad claims fail with some probability. Though not shown in detail here, the results still hold.

[5]This follows the issuer-pay scheme.

[6]This fee assumption captures the issuer-pay scheme. For the choice of not being evaluated by the CRA,

decides a screening effort level t with constant marginal cost b to evaluate the signal received. With probability $p_d(t) = 1 - e^{-t}$, the window dressed signal is detected. This probability function shares a similar feature with the window dressing probability function $p_w(q)$. The greater the effort t that the CRA makes, the more likely it is that window dressing is discovered. The marginal probability is decreasing in t i.e., $p'_d(t) > 0$ and $p''_d(t) < 0$. Again, $p_d(0) = 0$ and $p_d(\infty) = 1$, and the CRA will devote a positive but finite screening effort.

Note that this screening probability function does not involve the quality distribution of financial claims λ. The reason for this specification is that the CRA does not know the quality of each financial claim in advance and has to evaluate all the signals with equal effort. No matter how good the average quality is, the CRA needs to devote the same effort to detect window dressing. We further assume that the CRA gives ratings truthfully, depending on the signal it receives after screening. If it observes a good signal after screening, the CRA gives a good rating to the claim. If it observes a bad signal, on the other hand, the CRA gives a bad rating. By doing so, it excludes the possibility that the CRA manipulates and misreports the rating. Instead, the screening effort level t indirectly captures the CRA's manipulation.

Once the rating is given, competitive investors purchase the claim at a price perfectly determined by the CRA's rating i.e., investors are uninformed and trust the CRA's evaluation.[7] Investors earn zero expected profit from either buying high-rated claims or low-rated claims due to the competition.

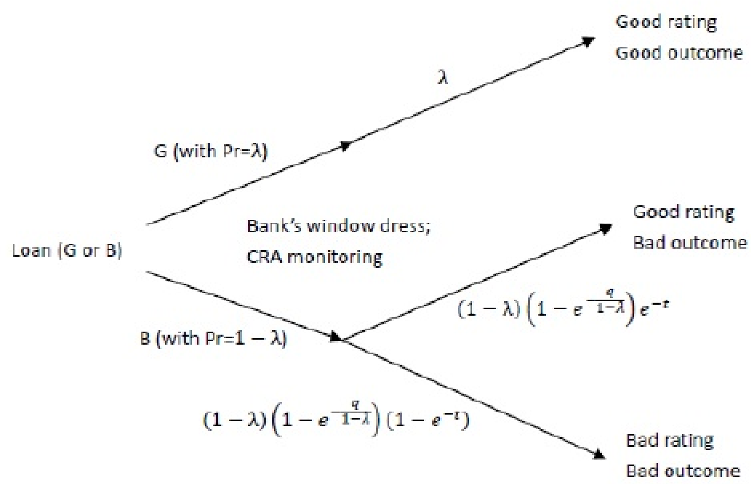
Finally, the values of the financial claims are realized and everything is paid out following the initial pricing rules. The timing described above is summarized in Figure 2.1.

When the issuer issues a good claim and investors believe that it is a good one, the issuer gets a commission fee of B. When the issuer issues a bad claim and investors believe

a relaxed assumption can be that without evaluation, the financial claim will be treated as a bad type claim. The results should be qualitatively similar.

[7] In this model, we focus on the moral hazard problem on the CRA side through its choice of evaluation effort t. Thus, we do not explicitly introduce opportunistic CRAs, which may report ratings different from the signal they perceive as modeled in Mathis et al. (2009). However, it is incorporated as the extreme case in which the CRA devotes zero effort for screening.

Figure 2.1: Timing of the Game



it to be bad, the issuer gets a commission fee δ. When the issuer issues a bad claim, but investors misperceive it as a good one, the issuer gets benefit Δ, where $\Delta > \delta$. The idea here is that when a financial claim is over-evaluated, the issuer gets more benefit than under precise valuation. Therefore, the issuer has incentive to window-dress in order to gain extra benefit.[8] Here, these three benefits are exogenously given for illustrative purposes. We extend the discussion by endogenizing them in Appendix A.3. The results are very similar.

Then, the CRA decides a screening effort level t to evaluate all claims submitted, which results in a probability $1 - e^{-t}$ that the manipulated signal can be detected with constant marginal cost b.

Investors are uninformed and purely trust the evaluation provided by the CRA. Here, we do not explicitly discuss the investors' behavior. Instead, we assume that investors are competitive and gain zero expected profit when buying claims. The price of each claim is determined by the zero expected profit conditions for competitive investors. Once the rating is released to the public, the commission fee/benefit will be realized, depending on the rating that the claim receives.

[8] I do not make any assumption about the relative magnitude between Δ and B. Any relation is possible. For the case where $\Delta > B$, it simply means that issuing an over-evaluated low-quality claim leads to a higher profit than when issuing a high-quality claim, which is very likely.

Following the issuer-pay scheme, assume that the CRA gets a fixed credit rating fee f from the issuer.[9] When the CRA fails to screen out a bad project, assume that it incurs a reputation loss L. This is a reduced form capturing the CRA's incentive for devoting effort and giving precise ratings.[10] We can think of this reputation loss as a loss in trust in its future ratings. The more mistakes the CRA makes, the more reputation loss it incurs and, consequently, the less benefit it will gain in the future.

Once the claims are rated and each has been bought by investors at the price determined by its rating, the outcome will be realized. Everything is paid out according to the contract.

In this model, there exists two-sided moral hazard. On one side, the CRA cannot observe the issuer's window dressing effort q. On the other side, investors cannot observe the CRA's screening effort t. Only the final outcome of each financial claim is observed by all players. There are three possible outcomes: 1) The good claim receives a good rating with probability λ. In this case, the issuer gets B and the CRA maintains its reputation. 2) The bad project receives a bad rating with probability $(1-\lambda)\left[1-(1-e^{-\frac{q}{1-\lambda}})e^{-t}\right]$. In this case, the issuer gets δ and the CRA maintains its reputation. 3) The bad project receives a good rating with probability $(1-\lambda)\,(1-e^{-\frac{q}{1-\lambda}})e^{-t}$. In this case, the bank gets the private benefit Δ and the CRA suffers a reputation loss L. Assume that $L > \Delta - \delta$, indicating that it is inefficient for the economy when window dressing occurs.[11]

The issuer chooses its effort, q, to maximize its expected profit

$$\max_q \lambda B + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}\Delta + (1-\lambda)[1-(1-e^{-\frac{q}{1-\lambda}})e^{-t}]\delta - aq - f \tag{2.1}$$

where λB represents the expected benefit gained from the case with a good claim; $(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}\Delta$ is the expected benefit gained from the case with an overrated bad claim;

[9] Since the fee f is paid unconditionally in this setting, it does not affect either the issuer's or the CRA's effort decision. I can also follow the literature by assuming that the fee is paid only when the issuer obtains a good rating, and the results are qualitatively similar.

[10] Later, I will model this reputation loss explicitly in a dynamic setting.

[11] I assume that the CRA cannot impose penalties on the issuer to penalize window dressing.

$(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}\Delta$ represents the expected benefit gained from the case with a precisely rated bad claim. Meanwhile, the issuer incurs effort costs aq when devoting effort q and pays a fixed fee f to the CRA.

The CRA chooses its screening effort, t, to maximize its expected benefit

$$\max_t f - bt - (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L \tag{2.2}$$

There are three parts to the CRA's objective function: 1)gaining a fixed fee f from the issuer; 2) paying screening effort costs bt; and 3) incurring a expected reputation loss $(1-\lambda)(1-e^{-q})e^{-t}L$ for failing to detect the issuer's window dressing.

Since investors are competitive, they gain zero expected benefit for buying both good-rated and bad-rated claims. Here, we assume that there are many projects to be rated, so a rating from one project will not affect the payment scheme. Thus, the investors' behavior is not modeled. In the Appendix A.3, we explicitly model the investors' IR constraint to endogenously determine B, Δ and δ.

2.3 Main Results

2.3.1 The First-Best Benchmark

First, we will discuss a benchmark case in which there is no asymmetric information, and both q and t are observable and contractible. For this case, since everything is known and contractible, the joint surplus of the issuer and the CRA will be maximized.[12] The CRA will have perfect information about the original signal, which truly reflects the claim quality. The CRA will observe any window dressing effort from the issuer, and it will be purely inefficient i.e., it will not change the CRA's perception of the claim quality. Because window dressing itself is costly for the issuer, the optimal effort from the issuer is $q^{FB}=0$. At the same time, since everything is observable, the CRA can observe the actual signal.

[12]Since competitive investors earn zero expected profit anyway, the joint surplus of the whole economy is also maximized in this case.

Thus, the issuer's optimal manipulation effort is $t^{FB} = 0$. This simple result is summarized in the following proposition.

Proposition II.1. *The first-best solution is* $q^{FB} = t^{FB} = 0$. *Under such efforts, the joint surplus is maximized.*

Proof. Because both q and t are observable and contractible, the objective is to choose q and t to maximize the joint surplus of the issuer and the CRA i.e.,

$$\begin{aligned}&\max_{q,t} \lambda B + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}\Delta + (1-\lambda)[1-(1-e^{-\frac{q}{1-\lambda}})e^{-t}]\delta \\ &-aq - bt - (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L \end{aligned} \tag{2.3}$$

Since $L > \Delta - \delta$, it is easy to show that this objective function is maximized when $q^{FB} = t^{FB} = 0$. The joint surplus equals $\lambda B + (1-\lambda)\delta$. [13] □

The key insight of this model is that there exist two pieces of asymmetric information: the CRA cannot observe the issuer's window dressing effort q, and investors cannot observe the CRA's screening effort t. Once there is no information asymmetry and the efforts are observable and contractible, the joint surplus can be maximized by conditioning on observable efforts. Then, the issuer will not manipulate or window dress at all. In turn, there is no need for the CRA to screen.

2.3.2 The Second-Best Solution

In the previous section, we discussed the benchmark case in which there is no asymmetric information and both q and t are contractible. In that case, the first-best outcome is achieved with $q^{FB} = t^{FB} = 0$, and the joint surplus is maximized. In this section, we will discuss the general case in which q and t are observed only by the player who makes the effort but are not observed by others. In this case, the payment cannot be contracted upon the efforts

[13] The joint surplus should be equal to the average value of the claim i.e., $\lambda v_G + (1-\lambda)v_B$. With this specification, the notation is a bit confusing.

directly and, instead, can only be linked to the realized outcomes. Players are to choose their effort level to maximize their own objective functions separately.

Recall that the issuer's and the CRA's objective functions are

$$\max_q \lambda B + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}\Delta + (1-\lambda)[1-(1-e^{-\frac{q}{1-\lambda}})e^{-t}]\delta - aq - f$$

$$\max_t f - bt - (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L$$

The second-best equilibrium can be derived from the following FOCs of each player:

$$e^{-\frac{q}{1-\lambda}}e^{-t}\Delta - e^{-\frac{q}{1-\lambda}}e^{-t}\delta - a = 0 \tag{2.4}$$

and

$$-b + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L = 0 \tag{2.5}$$

i.e.,

$$e^{-\frac{q}{1-\lambda}}e^{-t}(\Delta - \delta) = a \tag{2.6}$$

where the left-hand side represents the marginal benefit of window dressing and the right-hand side is the marginal cost of doing so.

Meanwhile,

$$(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L = b \tag{2.7}$$

where the left-hand side is the marginal benefit of screening to avoid reputation loss and the right-hand side equals the marginal cost of doing so.

Lemma II.2. $\frac{dq}{dt} < 0$ *and* $\frac{dt}{dq} > 0$.

Proof. By taking the derivative of the CRA's screening effort t on the issuer's best response function (Equation 2.6) and the derivative of the issuer's window dressing effort q on the

CRA's best response function (Equation 2.7), respectively, we have that

$$\begin{aligned} -\frac{q}{1-\lambda}e^{-\frac{q}{1-\lambda}}e^{-t}(\Delta-\delta)\frac{dq}{dt} - e^{-\frac{q}{1-\lambda}}e^{-t}(\Delta-\delta) &= 0 \\ e^{-\frac{q}{1-\lambda}}e^{-t}L - (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L\frac{dt}{dq} &= 0 \end{aligned}$$

Thus,

$$\begin{aligned} \frac{dq}{dt} &= -\frac{e^{-\frac{q}{1-\lambda}}e^{-t}(\Delta-\delta)}{\frac{q}{1-\lambda}e^{-\frac{q}{1-\lambda}}e^{-t}(\Delta-\delta)} = -\frac{1-\lambda}{q} < 0 \\ \frac{dt}{dq} &= \frac{e^{-\frac{q}{1-\lambda}}e^{-t}L}{(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L} = \frac{e^{-\frac{q}{1-\lambda}}}{(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})} > 0 \end{aligned} \tag{2.8}$$

□

The intuition for this lemma is straightforward. An increase in the CRA's screening effort will make the issuer's window dressing more likely to be detected, thus disincentivizing its window dressing motive. For the CRA, on the other hand, the issuer's greater attempt to window dress will cause the CRA to screen more carefully. From this lemma, it is known that the issuer's and the CRA's strategies are neither strategic substitutes nor strategic complements, which is different from the results shown in Cohn et al. (2013). At the same time, we know that there exists a unique pure-strategy equilibrium. Therefore, the model is not complicated by the multiple equilibria, as in Cohn et al. (2013).

From the first-order conditions, the second-best solution is characterized in the following proposition.

Proposition II.3. *When the window dressing effort q and the screening effort t cannot be observed by other players and cannot be contracted on directly, the second-best equilibrium* *efforts from the issuer and the CRA are*

$$
\begin{aligned}
q^{SB} &= \min\{(1-\lambda)\ln[1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}], (1-\lambda)\ln\frac{\Delta-\delta}{a}\} \\
t^{SB} &= \max\{-\ln[\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L}], 0\}
\end{aligned} \tag{2.9}
$$

Proof. To achieve the equilibrium, the first-order conditions are satisfied for interior solutions. At the same time, we know that these two efforts must be non-negative i.e., $q, t \geq 0$.

From 2.6, we have

$$e^{-\frac{q}{1-\lambda}}e^{-t} = \frac{a}{\Delta-\delta}$$

Plug it into 2.7 and rearrange the equation, and we have

$$(1-\lambda)e^{-t}L = b + \frac{a}{\Delta-\delta}(1-\lambda)L$$

Thus, we derive that

$$t = -\ln[\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L}] \tag{2.10}$$

Plugging it back into 2.6, we can solve q out as

$$q = (1-\lambda)\ln[1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}] \tag{2.11}$$

In addition, these two efforts must be non-negative. From Equation 2.11, it is easy to see that $q > 0$, because $(1-\lambda) > 0$ and $1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a} > 1$ (thus, $\ln[1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}] > 0$). Meanwhile, $t \geq 0$ only if $\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L} \leq 1$.

When $\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L} > 1$, the CRA will choose a screening effort level of zero. In turn, from the issuer's best response function, for such a case, the issuer will choose its window dressing effort to be $(1-\lambda)\ln\frac{\Delta-\delta}{a}$.

In sum, the second-best equilibrium can be summarized as

$$
\begin{aligned}
q^{SB} &= \min\{(1-\lambda)\ln[1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}], (1-\lambda)\ln\frac{\Delta-\delta}{a}\} \\
t^{SB} &= \max\{-\ln[\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L}], 0\}
\end{aligned}
$$

□

In the following, we will focus on discussing about the interior solution, which is of more interest. Thus, the following assumption is made.

Assumption 1: $\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L}\leq 1$.

The intuition for this assumption is that the sum of the cost-benefit ratios of the issuer and the CRA cannot be too big. This assumption implicitly incorporates two additional restrictions i.e., $\frac{a}{\Delta-\delta}<1$ and $\frac{b}{(1-\lambda)L}<1$, which mean 1) that the marginal cost of window dressing a cannot exceed the maximum marginal benefit gained from the window dressing, $\Delta-\delta$; and 2) that the marginal cost of screening b cannot exceed the maximium marginal benefit gained from avoiding reputation loss, $(1-\lambda)L$. These two restrictions are weaker than Assumption 1, because Assumption 1 also requires that these two cost-benefit ratios together cannot exceed 1. The idea is that in order for both the issuer and the CRA to devote effort, the incentive (i.e., the benefit-cost gap) must be large enough for both at the same time.

Before moving to the discussion about comparative statics, we want to highlight the link between the first-best equilibrium and the second-best equilibrium. The incentive for the issuer to misbehave and to window dress comes from the benefit that it could gain from cheating successfully. The maximum benefit it can possibly gain from window dressing equals $\Delta-\delta$. When such a net gain goes to zero, the second-best equilibrium will convert to the first-best outcome. This can be easily seen from Equation (9). When $\Delta-\delta\rightarrow 0$, $q=(1-\lambda)\ln[1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}]\rightarrow 0$ i.e., the issuer does not window dress at all. Consequently, since the issuer does not window dress, there is no need for the CRA to screen and, thus, $t \to 0$.

Corollary II.4. *When Assumption 1 is satisfied and* $\Delta - \delta \to 0$, $q^{SB} \to q^{FB}$ *and* $t^{SB} \to t^{FB}$. *When* $\Delta - \delta = 0$, $q^{SB} = q^{FB}$ *and* $t^{SB} = t^{FB}$.

Proof. The result follows immediately after taking $\Delta - \delta \to 0$ in representations of q^{SB} and t^{SB}. □

This corollary provides a possible solution to avoid window dressing by shrinking the net benefit $\Delta - \delta$. This may work by setting a low benefit for even good-rated claims, but this pricing strategy will disincentivize the issuer from issuing high-quality claims and may not be a good idea for the economy as a whole. An alternative interpretation is that window dressing can also be avoided if a punishment could be imposed on the issuer once the actual claim quality is realized (e.g., a claw-back scheme).

Next, we will discuss the comparative statics of the model parameters for the interior solution, which are summarized in the Corollary below.

Corollary II.5. *When Assumption 1 is satisfied, the comparative statics of the second-best equilibrium are*

$$
\begin{aligned}
\frac{dq}{da} &< 0, \frac{dt}{da} < 0; \\
\frac{dq}{db} &> 0, \frac{dt}{db} < 0; \\
\frac{dq}{d(\Delta - \delta)} &> 0, \frac{dt}{d(\Delta - \delta)} > 0; \\
\frac{dq}{dL} &< 0, \frac{dt}{dL} > 0; \\
\frac{dq}{d\lambda} &> 0, \frac{dt}{d\lambda} < 0
\end{aligned}
$$

Proof. Here, we show only the proof for comparative statics of the issuer's marginal cost of window dressing. All others can be shown analogously.

$$\frac{dq}{da} = -\frac{(1-\lambda)}{1+\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a}}\frac{b}{(1-\lambda)L}\frac{\Delta-\delta}{a^2} < 0$$

$$\frac{dt}{da} = -\frac{1}{\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)L}}\frac{1}{\Delta-\delta} < 0$$

□

The effects of these parameter changes are very intuitive. For instance, when the issuer's marginal cost of window dressing a increases, it will be more difficult for the issuer to window dress its claim, and, thus, the window dressing effort q will be lower. In response, the CRA's screening effort t decreases. When the CRA's marginal cost of screening b is high, it will screen less and, in turn, the issuer will do more window dressing. When the net benefit of window dressing $\Delta - \delta$ increases, the issuer has more incentive to window dress and, thus, the CRA will devote more effort to screening. When the CRA's reputation loss from failing to screen adequately is high, the CRA is willing to devote more effort to avoid such loss. With this expectation, the issuer will window dress less.

The last parameter λ is of great interest in the following discussion. As derived from the Corollary, a better average claim quality results in a higher window dressing effort q and a lower screening effort t, which seems to be a bit counterintuitive at first glance. The intuition for this result is as follows: when the average quality is high, there are potentially fewer low-quality claims to be window dressed, leading the CRA to devoting devote less effort to screening. Given that, the issuer will window dress more. For the issuer, there are two effects: 1) direct effect: higher average quality makes window dressing less profitable; and 2) indirect effect: less screening effort makes window dressing more likely to succeed. The latter effect dominates the former and the net effect is positive.

2.3.3 Credit Rating Along Changes in the Fundamentals of the Economy

In this section, we will discuss in more detail one major result of this paper–how the issuer's and the CRA's strategies change when the fundamentals of the economy vary. As analyzed in the last section, the issuer increases its window dressing effort, and the CRA reduces its screening effort when the average quality of the financial claims issued improves. The average quality λ can be treated as a reduced-form way to capture the changes in economic fundamentals. When the economy is in a good state or a boom, there are more good and profitable financial claims of better average quality (higher λ). On the other hand, when the economy is in a bad state or a recession, the average profitablility will decrease and, accordingly, the average value of the financial claims will shrink (lower λ). In reality, there might be indeed some other changes that may affect λ during booms or recessions; in our setting, with financial claims of only binary type and normalized size, λ is a good proxy to capture economic conditions. Therefore, a direct result regarding economic fluctuations is summarized as follows.

Proposition II.6. *Under Assumption 1, the issuer has greater incentives to window dress when economic conditions are better. Correspondingly, the credit rating agency screens with lower intensity in such states.*

Proof. The result can be derived immediately by the taking derivative of *lambda* on equilibrium q and t. $\square$

Though the above proposition describes the behaviors of the issuer and the CRA, these behaviors alone are not enough to characterize the equilibrium. In order to do so, the competitive investors' posterior belief about the economic conditions, denoted as $\widehat{\lambda}$, must be greater than the ex ante belief about the economic conditions λ. With this belief change, the price of the highly rated claims is higher, which results in a larger benefit from window dressing. This, in turn, supports a stronger incentive for the issuer to window dress more i.e., $\frac{d\widehat{\lambda}}{d\lambda} > 0$. The following lemma confirms this.

Lemma II.7. $\frac{d\widehat{\lambda}}{d\lambda} > 0$.

Proof.

$$\begin{aligned}\widehat{\lambda} &\equiv \Pr(G|\text{Good rating received}) \\ &= \frac{\lambda}{\lambda + (1-\lambda)(1-e^{-\frac{q^{SB}}{1-\lambda}})e^{-t^{SB}}} \\ &= \frac{\lambda}{\lambda + \frac{b}{L}}\end{aligned}$$

Thus,

$$\frac{d\widehat{\lambda}}{d\lambda} = \frac{\frac{b}{L}}{(\lambda + \frac{b}{L})^2} > 0$$

□

Therefore, the behaviors characterized in the proposition above are indeed equilibrium behaviors.

2.3.4 Time-Varying Punishment

In the previous discussions, the CRA's reputation loss from failing to detect the issuer's window dressing, L, is assumed to be a constant and does not vary across different economic conditions. In reality, this reputation loss is highly likely to be correlated with current economic conditions. To be specific, during an economic boom, there is a smaller fraction of low-quality claims in the market, and investors can be more tolerant of the CRA's mistakes of overrating for two reasons. First, during a boom, there are fewer low-quality claims that need to be detected; thus, detecting bad claims will be more difficult. Once investors realize this fact, the CRA will not be punished too much and, thus, the reputation loss L should be low. Second, during a boom, even bad projects are less likely to fail, or, in other words, even bad claims are of greater value, thus, investors will be more tolerant of overrating, and the CRA's reputation loss will be lower. Therefore, to capture this possible time-varying punishment, we assume that $L = g(\lambda)$ where $g'(\lambda) < 0$.

For the issuer, the new equilibrium window dressing effort becomes

$$q^{SB\prime} = (1-\lambda)\ln[1+\frac{b}{(1-\lambda)g(\lambda)}\frac{\Delta-\delta}{a}]$$

and for the CRA, the new equilibrium screening effort is

$$t^{SB\prime} = -\ln[\frac{a}{\Delta-\delta}+\frac{b}{(1-\lambda)g(\lambda)}]$$

Lemma II.8. $\frac{dq^{SB\prime}}{d\lambda} > 0$, $\frac{dt^{SB\prime}}{d\lambda} < 0$.

Proof. The results follows right after taking the derivatives on $q^{SB'}$ and $t^{SB'}$. $\square$

Thus, altering the reputation loss to be time-varying does not change the behavior of the issuer and the CRA. The intuition is straightforward. During economic booms, there is less reputation loss when the CRA makes mistakes, and thus, the CRA tends to shirk and to devote less screening effort t. In turn, the issuer will increase its window dressing effort q even more. Meanwhile, to make sure that this is still equilibrium behavior, we also need to verify again that the posterior belief about economic conditions is an increasing function of the ex ante belief i.e., $\frac{d\widehat{\lambda}}{d\lambda} > 0$. Recall that

$$\begin{aligned}
\widehat{\lambda} &= \frac{\lambda}{\lambda+(1-\lambda)(1-e^{-\frac{q^{SB\prime}}{1-\lambda}})e^{-t^{SB\prime}}} \\
&= \frac{\lambda}{\lambda+\frac{b}{L}} \\
&= \frac{\lambda}{\lambda+\frac{b}{g(\lambda)}}
\end{aligned}$$

Thus, we must have

$$\begin{aligned}\frac{d\widehat{\lambda}}{d\lambda} &= \frac{\lambda + \frac{b}{g(\lambda)} - \lambda[1 - \frac{b}{g(\lambda)^2}g'(\lambda)]}{[\lambda + \frac{b}{g(\lambda)}]^2} \\ &= \frac{\frac{b}{g(\lambda)}}{[\lambda + \frac{b}{g(\lambda)}]^2}[1 + \frac{\lambda g'(\lambda)}{g(\lambda)}] \\ &= \frac{\frac{b}{g(\lambda)}}{[\lambda + \frac{b}{g(\lambda)}]^2}[1 + \varepsilon_\lambda] \\ &> 0\end{aligned}$$

which is equivalent to

$$\varepsilon_\lambda > -1,$$

where ε_λ represents the quality elasticity of the reputation loss, which is negative by definition. Therefore, to guarantee that the equilibrium behaviors are consistent, we must have the following assumption.

Assumption 2: $|\varepsilon_\lambda| < 1$.

The intuition for Assumption 2 is that reputation loss as a punishment to the CRA when it fails to detect the issuer's window dressing behavior, cannot be too sensitive to the change in economic conditions. This is very likely to be consistent with the current scheme in reality.

Proposition II.9. *When Assumptions 1 and 2 hold, the issuer devotes more effort to window dressing, and the CRA devotes less effort to screening during a boom (and vice versa).*

2.3.5 Psuedo Dynamics

After learning the strategic interactions between the issuer and the CRA in a static setting, it is meaningful to discuss the dynamic evolution and interactions between the issuer and the CRA, especially when economic conditions fluctuate over time. Instead of developing a full dynamic model to capture this, we introduce a simple psuedo-dynamic model to provide the main idea. Different from the static game discussed above, under this psuedo-dynamic setting, we introduce an additional information asymmetry by which the issuer has a relative information advantage over the CRA about the economic fundamentals. More specifically, we assume that the issuer knows the current λ_t at period t, but the CRA's perception about the economic condition comes purely from the one-period lag, $\widetilde{\lambda}_t = \lambda_{t-1}$. This additional information asymmetry captures the notion that the issuer may utilize its informational advantage to condition its window dressing attempts further.

I show that the issuer does not always use this information advantage and behaves differently when economic conditions change in different directions. Intuitively speaking, we learned from the last section that when economic conditions improve, the CRA devotes less screening effort and vice versa. When the issuer perceives the fundamental change before the CRA does, it may not want the issuer to be informed about this change, depending upon whether the change is positive or negative. When economic conditions become better, an update leads to less screening by the CRA, and, thus, the issuer will have the incentive to confirm the change with the CRA. On the other hand, when economic conditions become worse, an update results in more screening. Then, the issuer will not be willing to update this change and will pretend that everything is the same as before. By doing this, the issuer can avoid additional screening that is supposed to occur and will enjoy benefits from extra successful window dressing. The formal anlysis is illustrated in the following proposition.

Proposition II.10. *When the issuer has a one-period information advantage about the changes in economic conditions, it informs the CRA and updates the information in an asymmetric way. The CRA is informed only when economic conditions improve.*

Proof. Assume that the issuer learns the new economic condition at period t as λ_t, while the CRA still maintains its belief $\widetilde{\lambda}_t = \lambda_{t-1}$. Then, their new objective functions will be

$$\max_q \lambda_t B + (1-\lambda_t)(1-e^{-\frac{q}{1-\lambda_t}})e^{-t}\Delta + (1-\lambda_t)[1-(1-e^{-\frac{q}{1-\lambda_t}})e^{-t}]\delta - aq - f$$

$$\max_t f - bt - (1-\lambda_{t-1})(1-e^{-\frac{q}{1-\lambda_t}})e^{-t}L$$

FOCs are

$$e^{-\frac{q}{1-\lambda_t}} e^{-t}(\Delta - \delta) = a$$

$$(1 - \lambda_{t-1})(1 - e^{-\frac{q}{1-\lambda_t}})e^{-t}L = b$$

We can derive that

$$\begin{aligned}
\widetilde{q} &= (1-\lambda_t)\ln[1 + \frac{b}{(1-\lambda_{t-1})L}\frac{\Delta - \delta}{a}] \\
\widetilde{t} &= -\ln[\frac{a}{\Delta - \delta} + \frac{b}{(1-\lambda_{t-1})L}]
\end{aligned}$$

When $\lambda_t > \lambda_{t-1}$, $\widetilde{q} < q$ and $\widetilde{t} > t$, consequently,

$$\widetilde{\pi}_I < \pi_I$$

Then, the issuer has the incentive to update and inform the CRA about the economic change.

On the other hand, when $\lambda_t < \lambda_{t-1}$, $\widetilde{q} > q$ and $\widetilde{t} < t$, the issuer actually will lose some expected profits if it reveals the economic change i.e.,

$$\widetilde{\pi}_I > \pi_I$$

Then, the issuer will not inform the CRA about the economic change. $\square$

2.4 An Alternative Setting

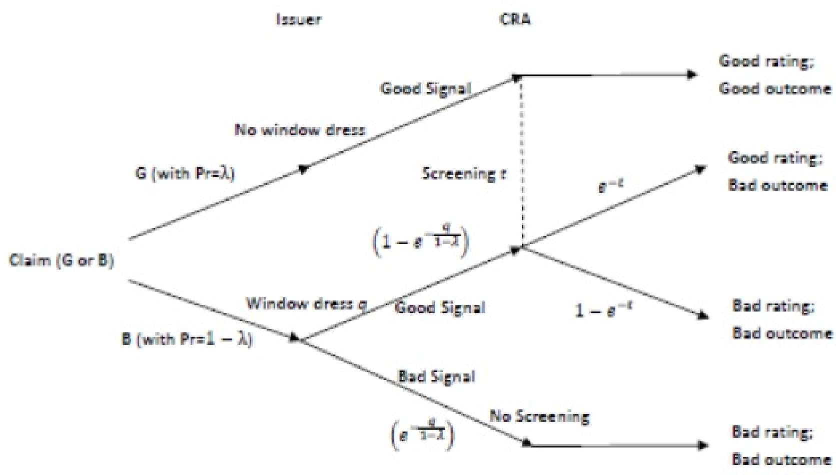
In previous sections, we assumed that the issuer makes its windowdressing decision without knowing the exact quality of each claim and has the same information as the CRA does. However, in reality, the issuer usually has, to some extent, an information advantage about the claims issued. Thus, to capture this information advantage, in this section, we instead assume that the issuer knows not only the distribution of claims to be issued (λ), but also the exact quality of each claim before determining its window dressing effort on each project. The new setting is as follows.

2.4.1 Setup

To begin with, there again exist one issuer, one CRA and competitive investors, all of whom are risk-neutral. The issuer has N financial claims to be issued. These claims are either good with value v_G or bad with v_B, $v_G > v_B$. The fraction of high-quality claims is λ, which is common knowledge and is known by every player. For each claim, the issuer also knows its exact type. Each project generates a signal, s^G for type G and s^B for type B, respectively. Before sending the signal to the CRA for evaluation, the issuer can choose to devote a window dressing effort q_i to project i with probability $\left(1 - e^{-\frac{q_i}{1-\lambda}}\right)$ to alter s^B into s^G. Different from the previous setting, the issuer learns the signals before window dressing. If it window dresses, it does so only for low-quality claims, since window dressing signals from high-quality claims do not result in any further benefit. The marginal cost of window dressing effort is $a > 0$, which is constant. Given that the probability of successfully window dressing equals $\left(1 - e^{-\frac{q}{1-\lambda}}\right)$, the same across all low-quality claims and marginally decreasing in terms of q, the issuer will put effort evenly on all low-quality claims. Thus number of successful window dressed signals N' follows a binomial distribution $B(p = 1 - e^{-\frac{q}{1-\lambda}}, (1-\lambda)\,N)$ with mean $(1 - e^{-\frac{q}{1-\lambda}})\,(1-\lambda)\,N$

After window dressing, all signals of all N claims are sent to the CRA for screening. At this point, the CRA observes two possible types of signals, s^G or s^B. When observing s^B, the claim is bad without any uncertainty and, thus, the CRA will give it a bad rating. When observing s^G, the claim can be either good or bad, which is unknown to the CRA. However, the CRA knows how many "window-dressed" claims are among them. Then, the CRA chooses screening effort t_j for claim j with a good signal s^G. The marginal cost for screening is constant and equals $b > 0$. The probability of detecting that a claim is window dressed with good signal s^G is $(1 - e^{-t_j})$, which is marginally decreasing in t. Therefore, the

Figure 2.2: Timing of the Revised Game



CRA will make the same effort t on all claims with good signal s^G. If detecting a window dressed claim, the CRA gives it a bad rating; otherwise, the CRA gives it a good rating.

Once ratings are given to claims to be issued, prices for high-rated claims and low-rated claims are determined by competive investors with zero expected benefit. For illustrative purpose, simply assume that when a high-quality claim is rated, the benefit for the issuer is B; when a low-quality claim is issued with a good rating, the issuer gets Δ; and when a claim is issued with a bad rating, the issuer gets δ.

Finally, the outcome of each claim issued is realized. Once the CRA makes a mistake on its rating, it gets a punishment L, which can be treated as a reputation loss. The new timing of the game is in Figure 2.2.

2.4.2 Objectives

The issuer choose effort level q to maximize its expected benefit

$$\max_q \lambda NB + \boldsymbol{E}[N'e^{-t}]\Delta + \boldsymbol{E}[N'(1-e^{-t})]\delta - (1-\lambda)\,Naq$$

where the first term represents the benefits from issuing high-quality claims; the second term represents the expected benefit from successfully issuing window dressed claims; the third term is the expected benefit from low-rated claims; and the last term equals the total costs of window dressing efforts.

For the CRA, once it has observed all signals, it also learns N', and then chooses the screening effort e to minimize its expect cost

$$\min_t N'e^{-t}L + (\lambda N + N')bt$$

where the former term is the reputation loss from failure of screenings, and the latter term is the costs of screening efforts.

2.4.3 Best Responses

Now, the game is a sequential game in which the CRA does not have perfect information, but the issuer does. Thus, we can use backward deduction. For the CRA, N' is the realized number of window dressed projects that is known and can be treated as a constant. By taking the first-order condition with respect to t, we have

$$-N'e^{-t}L + (\lambda N + N')b = 0$$

and, thus,

$$t = \ln[\frac{N'}{\lambda N + N'}\frac{L}{b}]$$

For interior solutions, we need $t > 0$. Therefore, $\frac{N'}{\lambda N + N'} > \frac{b}{L}$. [14]

For the issuer,

$$\max_q \lambda NB + \boldsymbol{E}[N'e^{-t}]\Delta + \boldsymbol{E}[N'(1-e^{-t})]\delta - (1-\lambda)\,Naq$$

[14] A sufficient condition is $L >> b$ i.e., the reputation cost, compared to the marginal cost of the screening effort, is large enough

plugging t back, we have

$$\begin{aligned}
&\max_q \lambda NB + \boldsymbol{E}[N'\frac{\lambda N + N'}{N'}\frac{b}{L}]\Delta + \boldsymbol{E}[N'(1-\frac{\lambda N + N'}{N'}\frac{b}{L})]\delta - (1-\lambda)\,Naq \\
= \;& \lambda NB + \lambda N\frac{b}{L}\Delta + \boldsymbol{E}[N']\frac{b}{L}\Delta + \boldsymbol{E}[N']\delta - \lambda N\frac{b}{L}\delta - \boldsymbol{E}[N']\frac{b}{L}\delta - (1-\lambda)\,Naq \\
= \;& \lambda NB + \lambda N\frac{b}{L}\Delta - \lambda N\frac{b}{L}\delta + (1-e^{-\frac{q}{1-\lambda}})\,(1-\lambda)\,N[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] - (1-\lambda)\,Naq
\end{aligned}$$

Taking derivative of q, we have

$$e^{-\frac{q}{1-\lambda}}N[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] - (1-\lambda)\,Na = 0$$

thus,

$$e^{-\frac{q}{1-\lambda}} = \frac{(1-\lambda)\,a}{\frac{b}{L}\Delta + (1-\frac{b}{L})\delta}$$

$$q = (1-\lambda)\ln[\frac{\frac{b}{L}\Delta + (1-\frac{b}{L})\delta}{(1-\lambda)\,a}]$$

2.4.4 Comparative Statics

In terms of the economic conditions parameter λ, we have

$$\frac{dt}{d\lambda} < 0$$

(if we treat the ex post N' as a fixed number).

Proposition II.11.

$$\frac{dt}{d\lambda} < 0$$

Proof. The proof is very straightforward.

$$\frac{dt}{d\lambda} = -\frac{N}{\lambda N + N'} < 0$$

□

Proposition II.12.

$$\frac{dq}{d\lambda}$$

is not monotonic, and there exists a threshold $\overline{\lambda}$*, such that*

$$\begin{aligned}
\frac{dq}{d\lambda} &> 0, \text{ when } \lambda < \overline{\lambda} \\
\frac{dq}{d\lambda} &= 0, \text{ when } \lambda = \overline{\lambda} \\
\frac{dq}{d\lambda} &< 0, \text{ when } \lambda > \overline{\lambda}
\end{aligned}$$

Proof.

$$\begin{aligned}
\frac{dq}{d\lambda} &= -\ln[\frac{\frac{b}{L}\Delta + (1-\frac{b}{L})\delta}{(1-\lambda)\,a}] + (1-\lambda)\,\frac{d[-\ln(1-\lambda)]}{d\lambda} \\
&= -\ln[\frac{\frac{b}{L}\Delta + (1-\frac{b}{L})\delta}{(1-\lambda)\,a}] + 1
\end{aligned}$$

Let $\frac{dq}{d\lambda} = 0$, we have

$$\overline{\lambda} = 1 - \frac{\frac{b}{L}\Delta + (1-\frac{b}{L})\delta}{ae}$$

When $\lambda < \overline{\lambda}$, $\frac{dq}{d\lambda} > 0$ and vice versa. □

2.4.5 The Issuer Retains a Fraction

We knows that due to information asymmetry, the issuer engages in window dressing in order to pursue higher profits. However, such window dressing attempts will hurt investors and may incur some welfare losses. In order to further alleviate such a problem, the regulator can force the issuer to retain a certain fraction of the claims it issues. Thus, the issuer will suffer part of the losses incurred by the window dressing, and in turn, the issuer will take this additional cost into account and will reduce its window dressing effort. In the following, we will discuss several different scenarios in which the remaining part can either be sold or not sold on the secondary market at different times.

To introduce the secondary market, we revise the game by adding one intermediate period. For the current setting, rather than selling everything to the investors after rating, the issuer is forced to hold α fraction of the claim. As before, the quality of a given claim is known to the issuer but not the CRA, and the investors know only the quality distribution of the claim. Again, the issuer will decide on a window dressing effort q for each low-quality claim, and the CRA will then choose a screening effort t on all claims with good signals. Then, the CRA will give ratings after screening, following the same route as before. Claims with good ratings will get a price of v_1^G in the intermediate stage and v_1^B for claims with bad ratings. In the last period, the final outcome of each claim will be realized. high-quality claims value v_2^G and low-quality claims, whether rated as good or bad, value v_2^B. For simplicity, assuming that $v_1^G = v_2^G$ and $v_1^B = v_2^B$. The CRA will be punished with reputation loss L if the final outcome indidates a low-quality claim with a good rating.

The CRA's screening response to the issuer does not change. The reason is that the CRA gives ratings depending on the screening of window-dressed signals and will be punished only on the realization of the final outcome of each claim. This is exactly the same as before. Formally, the CRA chooses

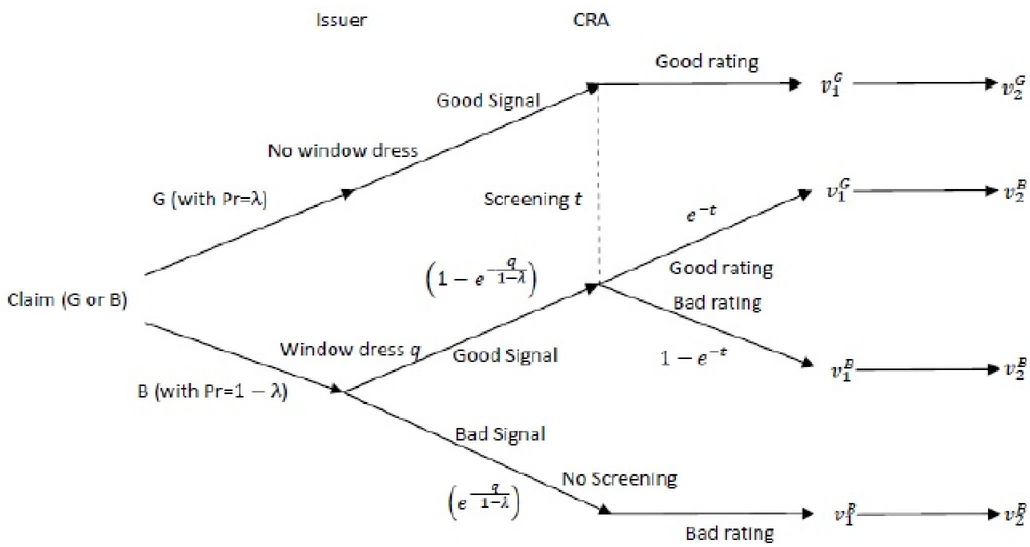
$$\min_t N'e^{-t}L + (\lambda N + N')bt$$

For the same realization of window-dressed claims N', the CRA's screening effort will be the same as the case without requiring the issuer to retain any share. However, it does not mean that, in equilibrium, the CRA's screening effort distribution (depending on the ex post realization of N') will also be the same. Rather, the CRA's screening effort will react passively to the change of the issuer's window dressing effort.

2.4.5.1 Forcing to Hold Until the End of the Game

The revised timing is shown in Figure 2.3. For the issuer, we first assume that α fraction must be held until the last period and cannot be traded. In that case, the issuer's new

Figure 2.3: Timing with Forced Holding



objective function is

$$\begin{aligned}
& \max_q (1-\alpha)\{\lambda NB + \boldsymbol{E}[N'e^{-t}]\Delta + \boldsymbol{E}[N'(1-e^{-t})]\delta\} \\
& +\alpha\{\lambda NB + \boldsymbol{E}[N'e^{-t}]\delta + \boldsymbol{E}[N'(1-e^{-t})]\delta\} - (1-\lambda)\, Naq \\
= \; & \lambda NB + (1-\alpha)[\lambda N\frac{b}{L}(\Delta-\delta)] + (1-\alpha)(1-e^{-\frac{q}{1-\lambda}})(1-\lambda)N[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta \\
& +\alpha(1-e^{-\frac{q}{1-\lambda}})(1-\lambda)N\delta - (1-\lambda)\, Naq
\end{aligned}$$

The only difference is that the issuer gets only δ for the retained fraction α when the claim is successfully window dressed.

F. O. C.

$$(1-\alpha)e^{-\frac{q}{1-\lambda}}N[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] + \alpha e^{-\frac{q}{1-\lambda}}N\delta - (1-\lambda)Na = 0$$

Thus, we have

$$\widehat{q} = (1-\lambda)\ln[\frac{(1-\alpha)[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] + \alpha\delta}{(1-\lambda)a}] < q^*$$

where q^* is the equilibrium from the case without retaining shares. The derivation above formally shows that the issuer will reduce its window dressing if it is forced to hold a certain fraction of issued claims since it needs to partially bear the window dressing cost in the end. It is also straightforward to show that the more retaining, the less window dressing i.e., the more costs being internalized, the less incentive the issuer has.

Lemma II.13. $\frac{d\widehat{q}}{d\alpha} < 0$

Proof.

$$\begin{aligned}\frac{d\widehat{q}}{d\alpha} &= (1-\lambda)\frac{-[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] + \delta}{(1-\alpha)[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] + \alpha\delta} \\ &= -\frac{(1-\lambda)\frac{b}{L}(\Delta - \delta)}{(1-\alpha)[\frac{b}{L}\Delta + (1-\frac{b}{L})\delta] + \alpha\delta} < 0\end{aligned}$$

□

With regard to the CRA, even though its best response function is the same as before, its screening effort, on average, will decrease because the issuer cuts its window dressing effort and the ex post realization of N' tends to be smaller.

2.4.5.2 Allowing the Issuer to Trade on the Secondary Market

Now, assume that the issuer holds α fraction of the claims at the intermediate period (e.g., investment banks hold shares during IPOs), but it can sell them on the secondary market before the final outcome is realized. We will discuss different scenarios in which the secondary market forms and prices in different ways, or the claims held by the issuer have different seniority.

Scenario 1: The issuer retains the same claims as those sold on the primary market. With probability ρ, investors encounter liquidity shocks and have to sell the high-rated claims that they bought on the primary market.

We know that in this case, the investors were forced to sell, and, at the same time, the issuer can also join the market to sell its holdings. However, the average quality of claims, excluding the issuer's will be $v^B < \widetilde{v} < v^G$ and the market price cannot reach a fair price for the high-quality claim. Therefore, the issuer sells only low-quality claims to the market but keeps the high-quality ones towards the end. Since the price on the secondary market will be greater than the value of bad claims, the issuer is always willing to sell the low-quality one.

Therefore, the average quality of the secondary market is

$$\Pr(\mathit{Good} \text{ in second market}) = \frac{\rho(1-\alpha)\lambda N}{\rho(1-\alpha)[\lambda N + E[N'e^{-t}] + \alpha E[N'e^{-t}]}$$

We know that when the price on the secondary market is higher than the fair price for this average quality, no one buys, and the price has to decrease to the fair price. On the other hand, if the price is equal to or less than the value of this average quality, investors buy, and the issuer sells only low-quality claims with good ratings.

Allowing the issuer to sell its holdings on to the market permits it to bear less window dressing cost by selling bad claims early on the secondary market. This will induce more window dressing incentives to the issuer i.e. larger than $\widehat{q}$ now, though not as much as the case without any forced holdings q^*.

$$\widehat{q} < q_1 < q^*$$

[15]

Scenario 2: "Branding" claims held by the issuer on the secondary market

In Scenario 1, buyers on the secondary market cannot distinguish whether the claims were bought from other investors or from the issuer. This results in the adverse-selection problem. Instead, if the claims held by the issuer are clearly labeled, then we know that the issuer's claims will be sold in an isolated secondary market, if at all. If the secondary market

[15] If there is no liquidity shock, since the participation of the issuer makes the pool of the secondary market worse, the investors cannot retain a zero expected profit from the secondary market due to the classical adverse selection ($E(v_{investor}) > P_{secondary} > v^B$), and the secondary market collapes.

price is below the fair price for the high-quality claims, only low-quality claims are sold by the issuer, and thus, no one buys. If the price is equal to the fair price for high-quality claims, no one buys either because the bought claims will be worth less than the price paid. Therefore, the isolated secondary market exists only if the price is set at the fair price for low-quality claims. If there is no discount over time, this case leads to the exact same payoff as the case with forced holdings.

$$q_2 = \widehat{q}$$

Scenario 3: Forced to hold junior claims only

If there is seniority difference between claims held by different players, and the issuer is required to retain only junior claims, we would expect the incentive for window dressing to be discouraged even further. The intuition is as follows. When the issuer is forced to hold junior claims, it can either hold them toward the end or sell them on the secondary market. However, due to adverse selection, the issuer again only wants to sell low-quality ones with good ratings (Note: again, the secondary market price will be equal to the price for low-quality claims). For these junior claims, the price will be even lower than the case without seniority difference. Whether or not the issuer holds or sells these, it gets paid less than in the case without seniority difference, which means it would be even more costly to window dress than it is in Scenario 1 i.e.,

$$q_3 < q_2 < q_1 < q^*$$

2.5 Extensions and Policy Implications

2.5.1 Asset Complexity

As Skreta and Veldkamp (2009) discuss, credit rating agencies may only over-rate assets with greater complexity. For example, prior to the 2008-09 financial crisis, assets such as mortgage-backed securities (MBS) were overrated but corporate bonds are rarely overrated.

Cornaggia et al. (2015) find supporting evidence that rating qualities differ across different asset classes. Skreta and Veldkamp (2009) use different variances of the signal to capture asset complexity and match this stylized fact under credit rating shopping with multiple CRAs. In our model, this feature can also be easily incorporated even without introducing multiple CRAs. To do so, we can introduce an additional parameter κ within the probability function for screening $1 - e^{-\frac{t}{\kappa}}$, called the "complexity parameter." The more complicated the claim, the larger κ is, thus the harder it is for the CRA to detect the window dressing done by the issuer.[16] We can easily derive the following lemma.

Lemma II.14. $\frac{dq}{d\kappa} > 0$, $\frac{dt}{d\kappa} < 0$.

The intuition is that more complicated financial claims require the CRA to devote more effort to detect the window dressing, given other things equal. Because screening is costly, the CRA will reduce its screening effort t and such a reduction will enhance the issuer's window dressing. In addition, introducing this complexity parameter does not alter our results on the effects of changes in economic conditions.

2.5.2 Credit Ratings Shopping

Another popular argument in the literature that cause the credit rating to be lax is that issuers shop around multiple credit rating agencies and disclose only the ratings that favor them. In our model above, we showed that even with only a single credit rating agency, the credit rating still can be boosted during economic booms. Here, we argue informally that introducing multiple CRAs and allowing for credit ratings shopping will only strengthen our results. To see this, assume that there are two CRAs in the market, and the issuer can choose which rating it wants to disclose. If these two CRAs are homogenous, then they devote the same effort to screening, and the probability that window dressing is detected with certainty becomes $(1-\lambda)(1-e^{-\frac{q}{1-\lambda}})(1-e^{-t})^2 < (1-\lambda)[1-(1-e^{-\frac{q}{1-\lambda}})e^{-t}]$. Therefore, the issuer will window dress more. With this new feature, when economic conditions improve, the

[16]The only caveat is that this is still a reduced form and cannot highlight the mechanism structurally.

issuer still increases its window dressing effort q; thus, the result is qualitatively maintained. Quantitatively, the issuer will increase its window dressing effort even more than in the single CRA case.

2.5.3 Market Discipline

In our model, the only tool used to displine the CRA's rating behavior is reputation, which needs to be good enough. However, reputation loss may not be a sufficient punishment, especially given the current credit rating agency market. As we know, there are only three major rating agencies (Moody's, S&P, and Fitch) with a total of 90% market share, and there exist substantial entry barriers deterring new entrants into the market. Investors will find it difficult to impose a harsh punishment when rating agencies make mistakes, since they have to turn back to these same rating agencies next time due to the lack of choices in the market. Some policy makers suggest introducing competition into the credit rating market, but then credit ratings shopping will be a new issue to be dealt with. In short, given the current market structure, such inefficiency is unavoidable. Given this drawback of market discipline through reputation concerns, ex post punishments may play a role, contributing to better regulation. Imposing additional ex post punishments on the issuer could restrict its window dressing incentives. On the other hand, imposing extra ex post punishments on the CRA could enhance its screening efforts.

2.5.4 Probabilities of Default

The above analysis above suggests some empirical and policy implications. As the model predicts, rating quality varies across different periods. Even with the same rating, financial claims rated under different economic conditions will have different probabilities of default. Specifically, financial claims with good ratings in good times have relatively higher default probability than good-rated claims in bad times. This prediction is empirically testable and has important policy implications. If this is the case, simply ignoring this fact will cause policy makers to underestimate the risk in good times and over estimate the risk in bad times. Appropriate risk-weighting may need to include factors over and above credit ratings.

2.5.5 Credit Spreads

As discussed above, default probabilities are time-varying for financial claims with the same ratings. The credit spread, which reflects the risk of each financial claim and depends on the average quality of claims within the same rating category, can also be time-varying. Specifically, the average quality of financial claims with good ratings is better in economic booms than in recessions. Therefore, the credit spread for good-rated claims during economic booms is lower. Given that the average quality of low-rated claims stays the same over time in our framework, the credit spread gap between claims with good ratings and those with bad ratings will be widened when economic conditions are better.

2.5.6 Transparency

In our framework, inefficiency stems from information asymmetry. To improve market efficiency, increasing transparency and reducing information asymmetry are essential. However, it is not an easy task because there exist two separate asymmetries: 1) between the issuer and the CRA and 2) between the CRA and investors. Compulsory disclosure from the issuer to the CRA can reduce the former asymmetry, but such a policy alone may not improve overall efficiency. Since the asymmetry between the CRA and investors does not disappear, simply removing information asymmetry between the issuer and the CRA will merely allow the CRA to enjoy information rent and it can still shirk in screening. On the other hand, a government-owned credit rating agency may help reduce the information asymmetry between the issuer and the CRA and increase the alignment between regulators and the CRA. Thus, the CRA may be more responsive in its screening, but the issuer's window dressing attempts cannot be totally excluded. In addition, Begley (2014) finds that transparency with standardized ratings may also incur some real costs. Therefore, the Dodd-Frank mandate to standardize ratings is difficult to enforce.[17]

2.6 Conclusion

Credit rating agencies were blamed for their inflated ratings during the 2008-09 financial crisis. Understanding how credit rating agencies perform when economic conditions vary is of great importance in better regulating the credit rating industry. In this paper, we present a two-sided moral hazard model for the credit rating market, in which a credit rating agency (CRA) detects window dressing by an issuer originating financial claims. We show that the credit rating agency monitors with lower intensity in such states. Correspondingly, the issuer has greater incentives to window dress when economic conditions are better. This is consistent with the fact that, prior to the recent crisis, credit rating agencies tended to overrate assets, especially mortgage-backed securities. In addition, we use a psuedo-dynamic model to characterize dynamic interactions between the issuer and the CRA. We show that when the issuer has an information advantage about economic fluctuations, it is willing to share the information with the CRA in an asymmetric way. Actual information will be shared only when economic conditions improve. When conditions worsen, however, the issuer will not inform the CRA. Instead, it will use the information advantage to induce less screening effort than should take place. Accordingly, the issuer will window dress even more.

A full dynamic model that precisely captures the dynamic evolution of the interactions between issuers and credit rating agencies would be desirable for future studies. At the same time, the simple but novel two-sided moral hazard model introduced in this paper can be applied to many other contexts in which a player interacts with an auditor/regulator. Examples include window dressing IPOs, corporate fraud, tax auditing, bank loan applications and so forth.

[17]However, the less information asymmetry there is, in practice, the lower the inefficiency can be.

CHAPTER III

Venture or Safety? Retirement and Portfolio Choice

3.1 Introduction

Baby-boomers, a large portion of the population in the U.S., have started their aging phase. As a result, the financial sustainability of the U.S. Social Security system is being significantly challenged. Thus, understanding retirees' portfolio choices, an important supplement to the government funded benefit systems, has drawn increasing attention, especially during the transition into retirement. Other than that, retirees' portfolio choices also affect other households' economic decisions, such as consumption and pension benefits and so forth. Understanding portfolio choice is, therefore, of great importance in formulating and implementing policies associated with retirement benefits. Conventional wisdom suggests that when retirees anticipate a substantial decrease in income after retirement, they should reduce their risk portfolio holdings when transitioning into retirement, shifting portfolio composition from risky assets to relatively safe ones. However, neither empirical nor theoretical evidence supports this argument. Whether and how this occurs remains a matter of debate. Though there are extensive theoretical studies about portfolio choice over the life cycle, the role that retirement plays on portfolio choice remains ambiguous.[1] From an

[1]The seminal works of Samuelson (1969) and Merton (1969, 1971) suggest that in a frictionless market, retirement status is irrelevant to portfolio choice. Bodie et al. (1992) show that, with non-tradable labor income, individuals tend to hold more risky assets while working than after retirement. On the other hand, Viceira (2001) shows that, with a large correlation between stock market risk and labor market risk,

empirical perspective, the retirement effect, to the best of our knowledge, is underexplored.[2] Since individuals' portfolio choices after retirement will affect their income flows, consumption and other economic decisions that are highly correlated with pension and retirement policies, it is worth exploring emipirical evidence on whether and how retirement might affect an individual's portfolio choice. To fill this gap in the literature, the goal of this paper is to empirically establish the causal effect of retirement on portfolio choice and to provide some possible explanations for this causal effect.

As we know, modeling and estimating models with endogenous retirement decisions pose economic and econometric challenges. To solve this endogeneity problem, we use data from the Health Retirement Study (HRS), a national longitudinal survey, and adopt the instrumental variable approach. We use two sets of instruments for retirement status: historical expected retirement status and eligibility age indicators of retirement benefits (especially, Social Security benefits). Using these instruments, we find that retirement causes a discrete jump in risky share holding by roughly five to seven percentage points. This increase accounts for one fourth of the increase in risk asset holdings, provided that the average risky share is 20.2 percentage points in our sample. This finding suggests a positive and sizable retirement effect on portfolio choice towards risky assets, which cannot be easily explained by the theories in existing studies.[3] Moreover, we further show that this positive shift mostly happens right after retirement immediately and it is mainly driven by the fact that households without risky assets start to hold risky assets after retirement.

Motivated by these counterintuitive findings, we further propose and test four hypotheses that may explain portfolio choice behaviors: 1) *The risk tolerance hypothesis:* provided risk tolerance is negatively correlated with risky asset holdings, when retirement itself increases

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portfolio choice can be riskier after retirement than prior to retirement. A detailed discussion on this stream of literature will be provided later.

[2]A partial list includes Heaton and Lucas (2000), Horneff et al. (2007), and Addoum (2013).

[3]For example, Samuelson (1969) posits that retirement is uncorrelated with portfolio choice; Bodie et al. (1992) predict a decrease in risky asset holdings right after retirement; Cocco et al. (2005) argue for a smooth increase in the risky asset share after retirement.

risk tolerance, risky asset holdings will increase;[4] 2) *The time spending hypothesis:* having more time after retirement to analyze or track risky asset markets such as stock markets can increase risky asset holdings. An alternative scenario under the same hypothesis could be that an increase in utility drawn from additional time working on risky assets could also increase risky asset holdings; 3) *The life expectancy hypothesis:* retirement results in a pessimistic view of life expectancy, which leads to an increase in risky asset holdings. Specifically, when people stop working, they may not feel as capable and active as before and may become pessimistic about their life expectancy, resulting in an increase in risky asset holdings. In particular, an increase (decrease) in life expectancy may cause an increase (reduction) in savings and, consequently, decrease (increase) the relative risky shares in the portfolio, as Cocco and Gomes (2012) predict; 4) *The bequest motive hypothesis:* retirement weakens the bequest motive and, thus, increases an individual's risky asset holding. To be specific, a weaker bequest motive increases the speed at which wealth is drawn down and, thus, decreases the wealth to labor income ratio. In turn, this will potentially result in an increase in risky portfolio choice, as predicted by Cocco et al. (2005). Though our results indicate that all four explanations can contribute to the retirement effect on portfolio choice to some extent, we predict that the risk-tolerance and time-spent hypotheses are likely the main driving forces.[5]

Our paper is most closely related to two main streams of the existing literature. The first stream discusses household portfolio choice under the life-cycle framework. Of relevance here are the seminal papers by Samuelson (1969) and Merton (1969, 1971). From there, follow-up studies have developed in two directions. Some studies do not explicitly model retirement based on life-cycle and, instead, only generally discuss portfolio choice over time (Calvet et al., 2009; Campbell, 2006; Heaton and Lucas, 2000). Other studies have focused on how portfolio choice is affected by demographic and behavioral characteristics, such as

[4] This is consistent with Canner et al. (1997).

[5] Our analysis captures only the net effects from retirement, and the explanations proposed here are just possibilities. Structurally decomposing contributions from different channels would be an interesting topic for future study.

age (Ameriks and Zeldes, 2004), health (Rosen and Wu, 2004; Edwards, 2008), lifetime experience of volatility (Malmendier and Nagel, 2011; Appendino, 2013), the expectation of future borrowing constraints (Guiso et al., 1996), optimism about investment decisions (Dominitz and Manski, 2007; Puri and Robinson, 2007) and financial literacy (Lusardi and Mitchell, 2007; Van Rooij et al., 2011).

There are a few papers that explicitly model retirement, either exogenously (Viceira, 2001; Campbell et al., 2001; Cocco et al., 2005; Gomes and Michaelides, 2005) or endogenously (Bodie et al., 1992, 2004; Farhi and Panageas, 2007; Dybvig and Liu, 2010) and focus on retirement transitions. For example, Cocco et al. (2005) build an exogenous retirement model and predict that, at retirement, individuals may smoothly adjust their risk portfolio holdings upwards. Farhi and Panageas (2007) endogenize an irreversible retirement choice and show a larger portion of risky assets prior to retirement. Gomes and Michaelides (2005) provide theoretical predictions that are close to our empirical findings. They use the Epstein-Zin utility function and include a fixed entry cost for risky investment, as well as risk aversion heterogeneities in their model. They find that with certain parameters, there can be a non-smooth shift in risky share at the exogenous retirement age of 65. While Gomes and Michaelides (2005) provide a possible scenario of portfolio choice changes close to retirement age, they provide very little explanation for this jump. From an empirical perspective, Addoum (2013) is the most relevant work on retirement portfolio choice. His work focuses on the correlation between retirement and portfolio choice by discussing relative bargaining power between the husband and wife in a household rather than by establishing causal effects. Addoum (2013) finds a negative correlation between retirement and risky portfolio choice, which is the opposite of our results. Also, the author finds a positive retirement effect of wives and a negative retirement effect of husbands, which also differs from our findings. However, Addoum (2013) focuses on the retirement effect interacted with marital status and discusses only the correlation between retirement and portfolio choices. Our paper contributes to the literature by empirically establishing a positive causality of retirement on portfolio choice and, further, discussing and testing possible explanations for this retirement effect. In addition, different from Addoum (2013), which considers only observations with positive risky shares, our analysis uses an unconditional sample and includes all observations. By doing so, our analysis is able to capture the household transition from non-risky asset holders to risky asset holders, and vice versa, and avoids the sample selection issue.[6]

Our paper is also related to a stream of studies that concentrate on other aspects of economic behavior besides portfolio choice around retirement. Some studies in this area discuss the "retirement consumption puzzle" i.e., a downward shift of consumption at retirement (Modigliani and Brumberg, 1954; Friedman, 1957; Heckman, 1974; Bernheim et al., 2001; Haider and Stephens, 2007; Battistin et al., 2009).[7] Other studies consider saving behavior (Papke, 2004), housing (Yogo, 2009), pension and annuitization (Brown, 2001) and health care (Hurd and McGarry, 1997). Our paper complements previous studies by empirically discussing household investment behavior during the retirement phase.

The remainder of this paper is organized as follows. Section 2 presents our empirical methodology, discussing our benchmark specification and identification strategy. Section 3 discusses data issues and variable definitions. Section 4 presents our main results on the retirement effect on portfolio choice. Section 5 investigates four possible hypotheses to explain the retirement effect. Section 6 conducts several robustness checks, and Section 7 concludes.

3.2 Empirical Methodology

3.2.1 Benchmark

We estimate the retirement effect on household portfolio choice. To this end, following a panel regression approach, we consider the benchmark regression as follows:

[6] In the data, we find that households that experience such transitions are not rare and account for approximately 20 percent of all households.

[7] Attanasio (1999) and Hurst (2008) provide excellent reviews on this topic.

$$Riskyshare_{it} = \beta_0 + \beta_1 HHretire_{it} + \boldsymbol{\gamma}'\boldsymbol{X}_{it} + \delta_i + \eta_t + \varepsilon_{it}, \tag{3.1}$$

where the dependent variable, $Riskyshare_{it}$, is household i's risky share at wave t, which is measured as the value of risky assets divided by the value of total financial assets. The key variable of interest, $HHretire_{it}$, is the head of household i's retirement status dummy at wave t. $\boldsymbol{X}_{it}$ contains sets of 1) household characteristics; 2) household head's characteristics; and 3) spouse's characteristics, for household i at wave t, under different specifications. Household fixed-effects, δ_i, capture time-invariant factors that are correlated to risk portfolio choice. η_t represents the wave fixed-effects, and ε_{it} is the time-varying unobserved disturbance. We focus on the retirement effect on risk portfolio choice, which is captured by β_1.

Note that the benchmark specification can estimate the average retirement effect, but it cannot provide enough information to help us distinguish between two competing sources for retirement effects. More specifically, we cannot separate the effects in terms of 1) those who switch from non-risky-asset buying to risky-asset buying after retirement (extensive margin); or 2) those who owned risky assets before and increase their risky asset holdings after retirement (intensive margin). To separate these possible features, we conduct two additional exercises. To test the extensive margin effect, we use a stock market participation indicator as the dependent variable to run a panel logistic regression model with a setting similar to that in Equation (1). To test the intensive margin effect, we follow Equation (1) by restricting our sample to households with positive risky shares in order to determine whether risky-asset holders increase their risky share after retirement. The results, together with ones for the benchmark regression, will be discussed in Section 3.

3.2.2 Identification Strategy

To establish the causal effect of retirement, we need to solve the endogeneity problem. Two sources of endogeneity could bias the estimate of the coefficient β_1: 1) omitted variable bias and 2) reverse causality. More specifically, omitted variable endogeneity occurs when unobserved factors such as preference and life style simultaneously affect the retirement decision and portfolio choice. Simultaneous endogeneity occurs when the affect is reversed and portfolio choices affect retirement decisions.

To address the endogeneity issue, we use the instrumental variable approach, which commonly requires two restrictions: 1) the relevance restriction, which requires that the instrumental variables are correlated to the endogenous variable namely, the household head's retirement status ($HHretire_{it}$); and 2) the exclusion restriction, which requires that the instrumental variable we use is uncorrelated to the error term ε_{it}, directly. To satisfy these two restrictions, we consider two sets of instrumental variables for retirement status.

The first instrument we use, following Haider and Stephens (2007), is the subjective expected retirement status. We construct this instrument by comparing the expected retirement age reported in the 1992 wave with the actual age in the following waves. If the expected retirement age is lower than the actual age, then the expected retirement status is classified as "retired." Otherwise, the status is "not retired." Based on the rational expectations argument, information known at time t is uncorrelated with the expectation errors between period t and future periods $t+1$, $t+2$, and so forth i.e., the instrument is uncorrelated with the error term in Equation (1). Meanwhile, the actual retirement is just a revised decision based on new and unexpected changes under a rational expectations assumption, which is highly correlated with self-reported retirement expectations in previous waves.[8]

Following Bonsang et al. (2012), we use the following two indicators as the second set of instruments: 1) whether an individual has reached the minimum age to claim early retirement benefits, and 2) whether an individual has reached the minimum age to claim full retirement benefits. Specifically, 62 is the minimum age at which an individual can claim partial Social

[8]The first-stage regression in Table A.8 in the Appendix A.5 ensures that the subjective retirement expectation is highly predictive of subsequent retirement behavior. For robustness, though not reported here, we construct an alternative expected retirement status by using the lagged expected retirement age instead of using only the expected retirement age from the 1992 wave. The results are qualitatively the same.

Security benefits i.e., early retirement,[9] and the age at which individuals can claim full Social Security benefits varies by different birth cohorts.[10] These two age thresholds are minimum age requirements for claiming partial and full Social Security benefits, respectively, and, consequently, are highly correlated with retirement decisions. The first-stage regression in Table A.8 in the Appendix A.5 confirms our conjecture. In terms of the exclusion restriction, since these two age thresholds are set by the government exogenously and are not affected by individuals, we argue that these age thresholds are relatively exogenous, and are not correlated with the error terms.[11]

3.3 Data Description

The data used in this paper are from the Health and Retirement Study (HRS), a longitudinal survey that collects detailed information on the US population over age 50.[12] More specifically, we use the RAND HRS Data file, a cleaned and processed version of the HRS data. RAND HRS data contain 26,000 household observations with detailed information on demographics, health, income, wealth, and retirement status. The main advantage of this database is that it includes 7,700 households, with at least one respondent of each household born between 1931 and 1941, who has retired or is expected to retire during the survey period (1992-2010).

Our primary sample draws from the 1992 wave to the 2010 wave in HRS. In order for our results to be comparable to those in the literature, we restrict our sample based

[9]75 percent Social Security benefits can be claimed at age 62, and the proportion increases over time until full benefits can be claimed.

[10]Note that the normal retirement age is set to increase to 67 over a 22-year period, which affects people born on or after January 2, 1938. Table A.7 in the Appendix A.5 shows the normal retirement age for the different cohorts used for our empirical analysis

[11]If the error term contains factors that affect an individual's life expectancy, the exclusion restriction may not necessarily hold.

[12]In terms of representativeness, although the HRS was designed to represent the US population over age 50, to address the research regarding racial and ethnic disparities, the HRS has oversampled Black and Hispanic populations. In this study, we do not adjust the sample regarding race and ethnicity; rather, we examine a subsample of only the white population. The results, though not reported, are qualitatively the same as our main results.

on the following four criteria: 1) a household with the head between ages 50 and 80;[13] 2) households not reporting self-employment; 3) households in which retirement status is known; 4) households with a risky share measure between 0 and 1. More detailed sample selection procedures can be found in Table A.5 in the Appendix A.5.

3.3.1 Variable Definitions

Retirement Status

Retirement status is the key variable of interest in our analysis. To measure the retirement status of each individual, we use the self-reported retirement status in the HRS, which is constructed from the survey question: *"At this time do you consider yourself to be completely retired, partly retired, or not retired at all?"* For the main analysis, we classify respondents who self-reported "completely retired" as retirees.[14] Figure 3.1 shows the portion of retirees by age. As the figure illustrates, the portion of retirees increases significantly between ages 62 and 65, which is closely related to the eligibility age for Social Security retirement benefits.[15]

Risky Shares

We define risky shares as the net value of stocks, mutual funds, and investment trusts divided by total financial assets. Total financial assets are the sum of checking and saving accounts; money market funds; certificates of deposit (CD); government saving bonds; treasury bills; corporate, municipal, government, and foreign bonds; and other savings after subtracting other debts, such as credit card balances, medical debts, and life insurance policy loans. Financial assets do not include main residence, other real estate, vehicles, businesses, and Individual Retirement Account (IRA) and Keogh plans.

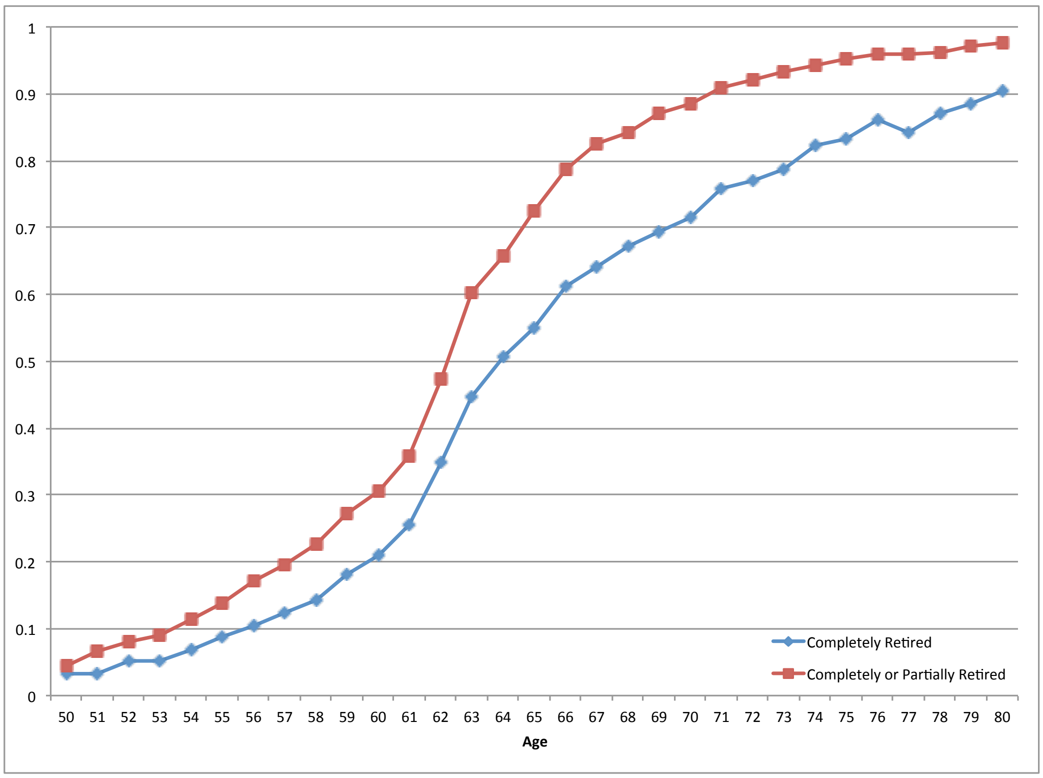
A caveat of the risky share measure in our main analysis is that, due to data limitation,

[13] We define the head of a household as the member who earns the most over the entire survey period.

[14] As an alternative measure of retirement, we treat both the completely and the partly retired groups as retirees. The results are robust.

[15] Other retirement measures constructed from a labor force participation question are constructed and tested as a robustness check in Section 6. The results are qualitatively the same.

Figure 3.1: Retirement Age



This graph is based on the aggregate samples in the HRS from the 1992 wave to the 2010 wave. To identify the retirement status, self-reported retirement status is used.

we do not include IRA accounts when calculating the risky share. Because the IRA assets account for a sizable fraction of retirement assets, excluding them may lead to a less precise risky share measure. However, the HRS did not collect information about IRA accounts until the 2000 wave. Even in the waves of 2000, 2002 and 2004, only limited information regarding the portion of stock investments in IRA accounts was collected in roughly three categories: *"Mostly or All Stocks, Mostly or All Interest Earning, and Evenly Split."* The exact portion of stocks in IRA assets has been collected only since the 2006 wave. To verify that our results are not driven by the construction of the risky share measure, we analyze a subsample since 2006 by including IRA accounts when measuring the risky share. The results, which are qualitatively similar, are reported in Section 6.

Expected Retirement Status

We construct the expected retirement status by following Haider and Stephens (2007). We first extract the expected retirement age information for each individual in the initial 1992 wave and then compare this expected retirement age to the actual age in the following waves. If an individual's expected retirement age is lower than the actual age in a given wave, we define this individual's expected retirement status as "expected to be retired." If an individuals's expected retirement age is higher than the actual age, we label the expected retirement status as "expected not to be retired."[16]

Indicators for Early Retirement and Normal Retirement

We define the indicator "early retirement" as 1 if an individual's actual age is greater than or equal to 62 and the other indicator, "normal retirement," as 1 if an individual's actual age is greater than or equal to the minimum age for claiming the full s]Social Security benefit, following Bonsang et al. (2012).

[16] As a robustness check, instead of using the expected retirement age reported in the 1992 wave, we also define an alternative expected retirement status by using the expected retirement age asked in one wave prior. Though not reported here, the results are qualitatively the same.

Measure of Risk Tolerance

The risk tolerance measures are constructed from the experimental survey questions regarding job choices, following Barsky et al. (1997). Specifically, in the 1992 wave, the risk tolerance is set using the following four levels, listed from least to most risk-averse:

- 1. *"R would take a job with even chances of doubling income or cutting it in half."*
- 2. *"R would take a job with even chances of doubling income or cutting it by a third."*
- 3. *"R would take a job with even chances of doubling income or cutting it 20%."*
- 4. *"R would take or stay in the job that guaranteed current income given any of the above alternatives."*

Based on the series of questions, the HRS classifies individuals into the four different groups, from the most risk-tolerant (scored as 1) to the least risk-tolerant (scored as 4).[17] These questions are not asked in the 1994 and 1996 waves. From the 1998 wave forward, additional questions are asked that allow two more categories:

- 1a. *"Less risk-averse than 1 above: R would take a job with even chances of doubling income or cutting it by 75%."*
- 4a. *"Between categories 3 and 4 above: R would take a job with even chances of doubling income or cutting it by 10%."*

These additional categories are used to define an alternative six-category risk-tolerance measure. We use both the four- and six-category risk-tolerance measures in our analysis.

Following the Stock Market

Stock market participation is costly. Time allocation is one type of cost that investors incur when they participate in the stock market, and we conjecture that reducing work hours

[17] For an easier illustration, we define the variable value in a reverse order. The larger the score, the more risk-tolerant.

allows households to devote more time to stock market and investment decisions. To capture this, we construct a measure for following the stock market. Since the 2002 wave, the HRS provides the amount of time allocated to the stock market using the question: *"How closely do you follow the stock market: very closely (1) , somewhat (2), or not at all (3)?"*. We use the answers to this question as a categorical measure for the frequency of following the stock market.

Life Expectancy

As discussed in Puri and Robinson (2007), individuals, who have higher self-reported life expectancies than the standard, are more likely to invest in stocks. We want to test whether the retirement effect is driven by a change in an individual's life expectancy. To do so, we define the life expectancy measures from two self-reported questions in the HRS.

- 1. *"The probability of living to age 75"*
- 2. *"The probability of living to age 85"*

We use these two reported probabilities as our life expectancy measures.

Probability of Leaving a Bequest

Although some economists are skeptical about the effect of the bequest motive on saving decisions (Hurd (1989); Dynan et al. (2002); Cagetti (2003)), it is more common to assume that investors with high bequest motives are likely to save more, and that this behavior in turn leads an individual to make riskier portfolio choices (Cocco et al. (2005); Rosen and Wu (2004)). To test whether the bequest motive changes near retirement, which can potentially explain the positive change in risky share, we use survey questions regarding the probability of leaving a bequest to construct bequest incentive measures. Beginning in the 1994 wave, the HRS asks the following question:

- 1. *"What are the chances that you [or your (husband/wife/partner)] will leave an inheritance totaling* $10,000 *or more?"*

If the respondent reports that the probability of leaving a bequest of $10,000 or more is larger than zero, he or she is further asked:

- 2. *"What are the chances that you [or your (husband/wife/partner)] will leave an inheritance totaling* $100,000 *or more."*

If the reported probability to the first question is zero, respondents are asked:

- 3. *"What are the chances that you (and your (spouse/partner)) will leave any inheritance?"*

We use these reported probabilities as our three measures for bequest motives.[18]

Other Control Variables

We use other demographic characteristics and financial status as control variables. One characteristic is age, which is one of the most important demographic traits in portfolio choice. The relationship between age and portfolio choice has previously been reported in the portfolio choice literature (Ameriks and Zeldes, 2004). We include age and age squared terms as control variables to distinguish the age effect from the effect of retirement. In addition to age, we control characteristics such as education, health status, ethnicity, religion, region of residence, and size of household, all of which may affect portfolio choice.

Classic portfolio theory assumes non-CRRA utility function and no labor income risk, so optimal portfolio share should be constant regardless of income and wealth level (Merton (1969); Samuelson (1969)). However, many studies have shown that level of income and wealth are important factors that affect an individual's portfolio decision (Cohn et al. (1975); Donkers and Van Soest (1999); Guiso et al. (2003); Peress (2004)). In light of these studies,

[18]Keep in mind that the first question is an "unconditional" measure and the last two are "conditional" measures, where the second question measures an even stronger bequest motive than that from the first question, and the last question is a weaker measure than that from the first question.

we control for the effect of financial status on the portfolio decision, using income level, wealth level, pension information, and mortgage status as control variables.[19]

3.3.2 Summary Statistics

Table 3.1 shows the summary statistics according to the retirement status of the household head.[20]

Part I of the table presents demographic characteristics, and part II summarizes the financial status. The average age of retirees is nine years older than that of non-retirees. A further difference is that retirees are less educated and less healthy than non-retirees. These differences are statistically significant. In terms of financial status, the average dollar value of total financial wealth for retirees is almost 50 percent larger than for non-retirees. After retirement, the income of the former is reduced by 42 percent, from an average of $41,000 to $23,800. While most of the summary statistics are consistent with the conventional wisdom, the risky shares show an opposite pattern. The stock share of financial assets for retirees is 2.8 percent higher than that of non-retirees, which amounts to almost a 15 percent increase. This difference in stock share is statistically significant, but the difference in combined stock share in financial and IRA assets between the two groups is not. The subjective measure of risk tolerance is also reported in the last two rows, but the difference is not statistically significant. Other risky shares, such as stock shares and other real estate shares, in total assets are also higher for retirees than for non-retirees.

To understand household asset composition in detail, we summarize the value of each asset and its portion of total household wealth in Table 3.2. As shown, housing assets constitute the largest portion of total wealth, while the second largest is financial assets, which are 19.6 percent of total assets. We also compare the asset composition of retirees and non-retirees. As shown in Table 3.2, there is no change in the relative importance of

[19] All wealth and income data are deflated by the consumer price index (CPI) into 2000 dollars.

[20] In this table, we report only some of the important variables in our analysis. The detailed summary statistics can be found in Table A.6 in the Appendix A.5.

Table 3.1: Summary Statistics

Variables	Non Retired Mean	Non Retired S.D.	Retired Mean	Retired S.D.	Difference Mean	Difference S.D.
Part I. Demographic Characteristics						
Age						
Head	60.2	6.43	69.6	6.45	-9.41	.044***
Spouse	58.7	7.77	66.8	7.77	-8.17	.060***
Size of Household	2.48	1.20	2.15	0.99	.336	.008***
Number of Children	3.09	1.96	3.21	2.08	-.120	.014***
Year of Schooling						
Head	13.2	2.93	12.5	3.13	.625	.021***
Spouse	12.7	2.87	12.3	2.67	.391	.022***
Self-Reported Health Status (Head)						
Head						
1:Poor/Fair, 0:Excellent/VeryGood/Good	.142	.349	.308	.462	-.166	.003***
1:Poor/Fair/Good, 0:Excellent/VeryGood/Good	.459	.498	.631	.483	-.171	.003***
Spouse						
1:Poor/Fair, 0:Excellent/VeryGood/Good	.207	.405	.245	.430	-.037	.003***
1:Poor/Fair/Good, 0:Excellent/VeryGood/Good	.513	.500	.553	.497	-.040	.004***
Part I. Financial Status						
Wealth ($10,000; 2000 Dollars)						
Total Asset	26.6	31.6	33.05	35.34	-6.41	.227***
Total Asset Excluding 2nd Residence	25.4	29.9	31.6	33.5	-6.20	.215***
Total Financial Asset	6.07	11.2	9.13	13.8	-3.06	.085***
Total Stock Asset	2.32	5.82	3.40	7.06	-1.08	.085***
Income ($10,000; 2000 Dollars)						
Total Income of Household	6.21	4.01	3.86	3.08	2.35	.025***
Total Income of Head	3.66	1.93	2.17	1.49	1.49	.012***
Total Income of Spouse	1.03	1.12	.683	.804	.344	.007***
Risky Share						
Stock Share in Financial Asset	.168	.305	.192	.322	-.024	.002***
Stock Share in Financial and IRA Asset	.231	.336	.233	.339	-.002	.003
Subjective Measure of Risk Tolerance						
1: Least Risk Averse; 4: Most Risk Averse	3.31	1.05	3.28	1.09	.028	.017
1: Least Risk Averse; 6: Most Risk Averse	4.64	1.49	4.70	1.55	-.058	.030

Notes: Wealth and income data are winsorized at the top 5 percent and bottom 5 percent level. The asterisk in the last column reports the significance of the t-test. The significant levels are as follows. *** Significant at the 1 percent level, ** Significant at the 5 percent level,* Significant at the 10 percent level.

Table 3.2: Summary of Household Assets

	Value of Assets ($1,000)					Composition of Assets				
	Mean	S.D.	Median	Min	Max	Mean	S.D.	Median	Min	Max
Total										
IRA	39.4	70.3	0.0	0.0	240	0.099	0.156	0.000	0.000	1.000
Stock	29.4	67.5	0.0	0.0	250	0.057	0.119	0.000	0.000	1.000
Financial Asset	78.5	132.4	17	-7.0	490	0.209	0.268	0.134	-1.000	1.000
Home Equity	103.0	98.4	75	0.0	350	0.419	0.296	0.384	0.000	1.000
Transportation	14.0	12.7	10	0.0	45	0.105	0.161	0.050	0.000	1.000
Business	5.4	21.4	0.0	0.0	100	0.013	0.058	0.000	0.000	0.996
Other Real Estate	15.5	42.2	0.0	0.0	170	0.038	0.106	0.000	0.000	1.000
Total Assets	322.6	372.6	179.5	0.0	1398	1.000	1.000	1.000	1.000	1.000
Non-retirees										
IRA	33.4	63.7	0.0	0.0	240	0.095	0.156	0.000	0.000	1.000
Stock	23.8	60.0	0.0	0.0	250	0.052	0.116	0.000	0.000	1.000
Financial Asset	62.5	116.6	12	-7.0	490	0.179	0.257	0.108	-1.000	1.000
Home Equity	94.7	94.5	69	0.0	350	0.429	0.296	0.402	0.000	1.000
Transportation	14.2	12.5	10	0.0	45	0.119	0.166	0.061	0.000	1.000
Business	6.3	22.8	0.0	0.0	100	0.016	0.067	0.000	0.000	0.996
Other Real Estate	15.6	42.0	0.0	0.0	170	0.043	0.115	0.000	0.000	1.000
Total Assets	284.7	347.1	152.0	0.0	1398	1.000	1.000	1.000	1.000	1.000
Retirees										
IRA	46.5	76.8	0.0	0.0	240	0.103	0.157	0.000	0.000	1.000
Stock	36.0	74.7	0.0	0.0	250	0.063	0.123	0.000	0.000	1.000
Financial Asset	97.2	146.5	25.5	-7.0	490	0.242	0.276	0.175	-1.000	1.000
Home Equity	112.8	101.9	87	0.0	350	0.408	0.295	0.360	0.000	1.000
Transportation	13.8	13.0	10.0	0.0	45	0.090	0.152	0.040	0.000	1.000
Business	4.4	19.5	0.0	0.0	100	0.009	0.046	0.000	0.000	0.745
Other Real Estate	15.3	42.6	0.0	0.0	170	0.032	0.095	0.000	0.000	0.999
Total Assets	366.4	395.5	220.0	0.0	1398	1.000	1.000	1.000	1.000	1.000

Notes: All asset values are winsorized at the bottom 5 percent and top 5 percent level and deflated into 2000 Dollars. We classify the samples into two groups, Retirees and Non-retirees, based on the self-reported retirement status of household heads. Households whose head reports *completely retired* are classified into Retirees, while households whose head reports *partially retired or not retired* are classified into Non-retirees.

each asset before and after retirement. However, the portion of each asset varies. The portion of relatively liquid assets, including financial, stock, and IRA assets, increases, while the portion of illiquid assets, such as home equity, transportation, business, and other real estate, decrease. In particular, the portion of financial assets shows the largest increase in both level and ratio.

3.4 Main Results

This section presents the main results of this paper. We will first discuss the results of the retirement effect on portfolio choice from the benchmark specification. After establishing the overall retirement effect, we further explore whether the retirement effect comes from the intensive margin i.e., individuals who do not hold risky assets before retirement tend to hold risky assets after retirement or from the extensive margin i.e., risky asset holders increase their risky portfolios after retirement. In addition, we investigate potential heterogeneities in terms of wealth, mortgage holdings, and pension holdings.

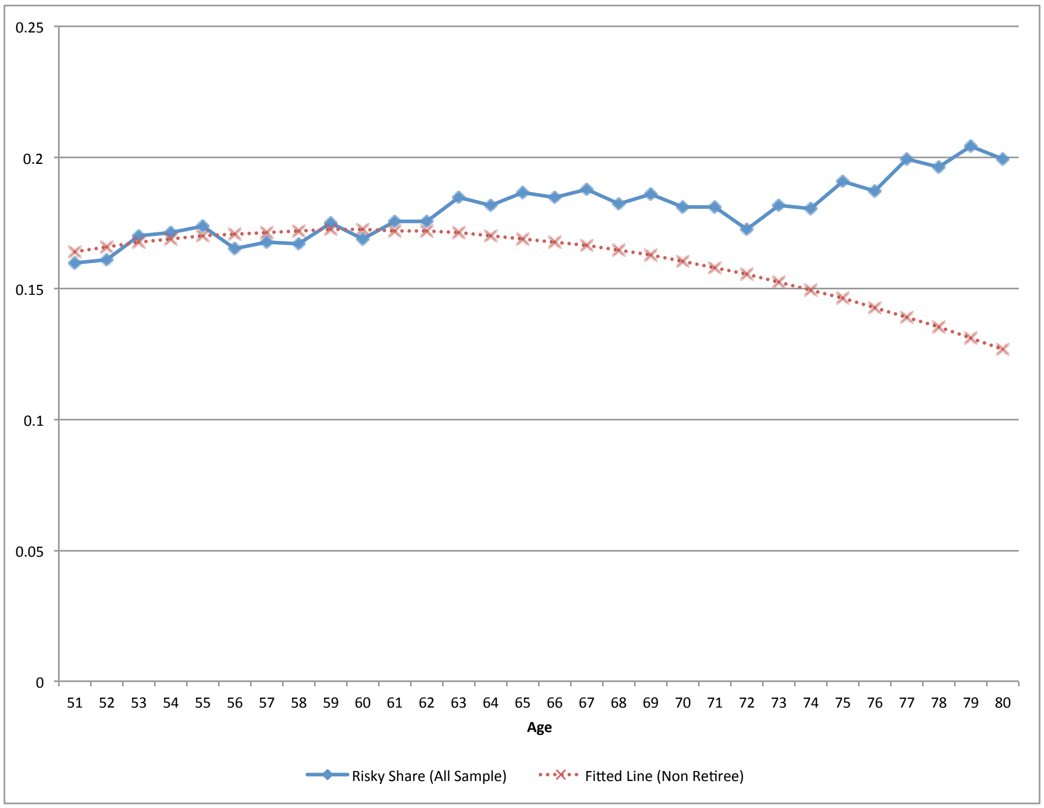
3.4.1 Benchmark Result

In this subsection, we discuss the overall pattern of retirement effects identified in the data. First, we present the rough pattern of how portfolio choice varies with age in Figure 3.2. The risky share increases between ages 62 and 67, when the portion of retirees increases dramatically. To distinguish the age effect from the retirement effect, we also draw the fitted line based on the estimated risky share of non-retirees by age. Since the retirement effect does not affect the fitted line, the gap between the fitted line and the real risky share can be partially explained by the retirement effect.

To further explore retirement effects, controlling for other factors that could affect portfolio choice, we consider the regression analysis described in Section 2. The results are summarized in Table 3.3. Column 1 provides estimates using the panel regression. Columns 2 to 4 report the estimates using a different set of instruments.[21] Columns 5-8 correspond to Columns 1-4 but include more control variables that capture the spouse's demographic characteristics, such as age, square of age, and self-reported health status. Standard errors are all clustered at the household level. Table 3.3 shows that the retirement effect is quite striking and robust across different specifications. The benchmark specification in Column

[21] The first-stage regression results of our instrumental variables are reported in Table A.8 in the Appendix A.5. All three instrumental variables that we use in this paper are, both economically and statistically, significantly correlated with the actual retirement status.

Figure 3.2: Risky Share by Age



This graph is based on the aggregate samples in the HRS from the 1992 wave to the 2010 wave. The risky share is the share of total value of stock in financial assets. To reduce the noise in the data, moving average (with ± 1 age window) is used. The non-retiree sample is used to estimate the fitted line, which shows the pattern of risky share by age. The formula for the fitted line is $RiskyShare = -0.2226 + 0.0132 * Age - 0.0001 * Age^2$.

1 shows that retired individuals invest approximately 1.3 percentage points more in risky shares, accounting for about 7.7% of the average risky share holdings. Taking into account that the estimates in Column 1 might be biased due to endogeneity issues, Columns 2-4 show that when the instrumental variables are used, the retirement effect increases by about 4.4-6.7 percentage points across different specifications. This accounts for 26% to 40% of the average risky shares. According to these results, retirement status has a huge impact on risky portfolio choices.[22]

Besides the positive retirement effect, we also find that control variables exhibit the effects, as we expected. Households with more wealth or higher income invest more in risky assets, which is consistent with predictions from Calvet et al. (2009). Over time, however, older individuals, in general, invest in risky assets, though this trend reverses at later ages, beginning around 77, consistent with findings in Campbell et al. (2001) and Cocco et al. (2005). Larger households invest less in risky assets, while households with more children have a higher percentage of risky shares in their portfolios. Though the sign of the coefficient is negative, self-reported health status has no significant impact on risky portfolio choice.[23] This differs from the findings of Rosen and Wu (2004), who find that health exhibits negative effects on risky portfolio choice. The difference between our results and those of Rosen and Wu (2004) might be due to different sampling periods and sample selection rules. While the sample for the benchmark analysis includes both married and single households, marital status changes during survey periods due to various reasons such as marriage, divorce, and death of spouse. Marital status change may affect risky investment behavior. To control for this effect, we include the dummy for marital status change: households that change martial status are indicated as "1," and households that remain the same are indicated as

[22]Because risky shares are nonnegative, we also estimate Tobit regression models. As shown in Table A.9 in the Appendix A.5, the results are robust across different specifications. We can observe that after retirement, individuals tend to increase their potential risky share holdings by 5.4 percentage points in the panel regression specification and 6.5 to 12.6 percentage points in different IV specifications. The results without controlling for the spouse's characteristics exhibit a similar pattern.

[23]For the robustness check, we also run the regression without controlling for the health status of household head or spouse. The results are similar to the benchmark table.

Table 3.3: Benchmark Table

	I				II			
	Panel	**IV1**	**IV2**	**IV3**	**Panel**	**IV1**	**IV2**	**IV3**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Head Completely Retired	0.013***	0.054**	0.044**	0.067***	0.015***	0.054**	0.052**	0.073***
	[0.003]	[0.022]	[0.019]	[0.019]	[0.004]	[0.024]	[0.022]	[0.021]
Head Age	-0.005*	-0.003	-0.009**	-0.002	-0.006*	-0.002	-0.011**	-0.001
	[0.003]	[0.006]	[0.004]	[0.006]	[0.003]	[0.007]	[0.004]	[0.007]
Head Age Square	0.000	-0.000	0.000*	-0.000	0.000*	0.000	0.000*	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Head Self-Reported Health	-0.000	0.002	-0.001	0.003	0.001	0.004	-0.000	0.004
(1:Poor/Fair, 0:Excellent/VeryGood/Good)	[0.003]	[0.005]	[0.003]	[0.005]	[0.004]	[0.006]	[0.004]	[0.006]
Household Size	-0.003**	-0.002	-0.003*	-0.002	-0.005**	-0.000	-0.004**	-0.000
	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]	[0.003]	[0.002]	[0.003]
Number of Children	0.005***	0.003	0.005***	0.003	0.009***	0.009***	0.010***	0.010**
	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]	[0.004]	[0.003]	[0.005]
ln(Household Income+1)	0.027***	0.038***	0.032***	0.041***	0.030***	0.042***	0.036***	0.045***
	[0.002]	[0.005]	[0.003]	[0.005]	[0.003]	[0.006]	[0.004]	[0.006]
ln(Household Wealth+1)	0.008***	0.008***	0.008***	0.008***	0.009***	0.009***	0.009***	0.009***
	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Change Marital Status	0.005	0.011	0.003	0.011	-0.014	0.030	-0.010	0.031
	[0.007]	[0.011]	[0.007]	[0.011]	[0.024]	[0.039]	[0.025]	[0.039]
Spouse Age Square					-0.000	-0.000*	-0.000	-0.000
					[0.000]	[0.000]	[0.000]	[0.000]
Spouse Self-Reported Health					-0.000	-0.008	-0.001	-0.008
(1:Poor/Fair, 0:Excellent/VeryGood/Good)					[0.003]	[0.005]	[0.003]	[0.005]
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86276	35444	81245	34826	65750	27888	61930	27421
R-square	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
F-Statistics	62.79	37.23	61.56	36.91	46.94	31.77	45.93	31.25
First Stage F-Statistics		608.92	392.03	282.39		600.45	384.03	278.98
Endogeneity Test Statistics		3.56	2.53	8.30		2.50	2.76	7.57
p-value		0.06	0.11	0.00		0.11	0.10	0.01

Notes: The dependent variable is a stock share in total financial assets. Both panel and IV regression results are reported. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

"0." The results show that marital status change does not affect the share of risky assets significantly.[24]

3.4.2 Retirement Duration

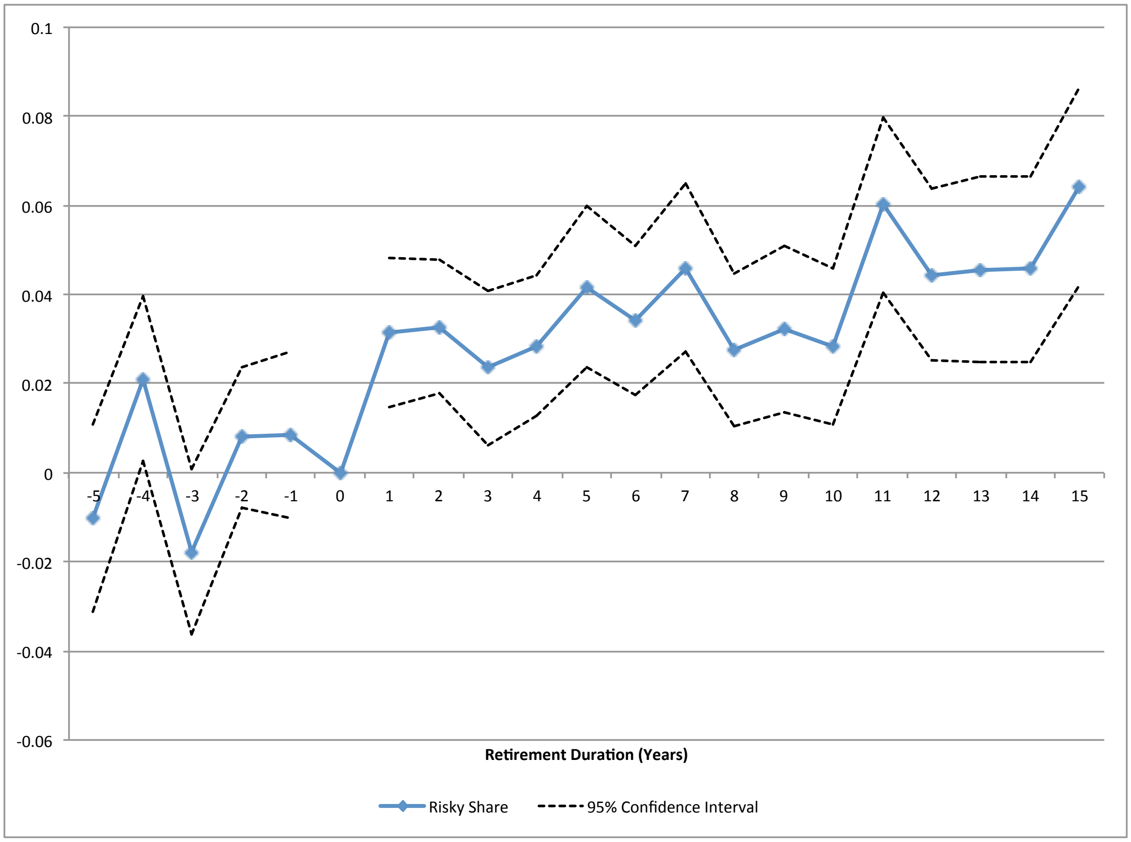
In the benchmark panel regression, we show that retirees hold larger risky shares in their portfolios than non-retirees do. Although this result is statistically significant and remains valid with various specifications, there is one limitation: this panel regression with a retirement dummy shows only that the overall share of risky assets throughout retirement is higher than that before retirement and is silent about how risky share changes due to retirement duration. To overcome this limitation and test how the share of risky assets changes due to retirement duration, we conduct an additional regression of the risky share on retirement duration dummies. The retirement duration is defined by the period between the interview year and the retirement year. For example, for retirees who participated in the 2010 wave survey and reported that they had retired in 2009, the retirement duration is one year in the 2010 wave. Because the HRS is a longitudinal survey, we can also estimate the retirement duration for individuals who are not retired in a particular survey wave, but report being retired in a later wave. In this case, the retirement duration is negative. This duration dummy regression tells us how the risky share changes over time after retirement. The regression equation to be estimated is:

$$Riskyshare_{it} = \beta_0 + \sum_{k=-4}^{15} \beta_{1k} D_{ikt} + \boldsymbol{\gamma}' \boldsymbol{X}_{it} + \eta_i + \epsilon_{it}, \tag{3.2}$$

where D_{ikt} is a dummy variable that indicates whether individual i has been retired for k years in year t (a retirement duration dummy), and other specifications are the same as in the benchmark regression. In this analysis, we restrict our sample to individuals whose retirement duration is between -5 and 15, and we omit the dummy for the retirement duration

[24] In addition to the marital status change, we also include marital status, whether single or married, as a control variable. Including marital status as a control variable instead of marital status change does not change the effect of retirement on stock share.

Figure 3.3: Coefficients of Retirement Duration in the Risky Share Regression



This graph is based on samples in the HRS from the 1992 wave to the 2010 wave. we restrict our sample to individuals whose retirement duration is between -5 and 15, and we omit the dummy for the retirement duration 0 to make these individuals the control group. The estimation equation is $Riskyshare_{it} = \beta_0 + \sum_{k=-5}^{15} \beta_{1k} D_{ikt} + \boldsymbol{\gamma}' \boldsymbol{X}_{it} + \eta_i + \epsilon_{it}$.

-5 to make these individuals the control group.

Figure 3.3 plots the coefficient β_{1k} and its 95% confidence intervals. As the figure illustrates, there is a distinct jump between the retirement duration 0 and 1. After the jump, the coefficients remain relatively stable. In other words, individuals increase their risky share at retirement and maintain that increase at the beginning of retirement and throughout retirement. On the other hand, coefficients prior to retirement are all insignificant. This result strengthens our hypothesis that retirement causes a discrete jump in risky share holdings.

3.4.3 Extensive Margin vs. Intensive Margin

In previous subsections, we have shown that there is a positive retirement effect on risky portfolio choice and this positive retirement effect is mainly contemporaneous right after retirement. In this subsection, we further investigate where this retirement effect comes from. To do so, we mainly investigate the retirement effect on extensive margin versus intensive margin.

To test the extensive margin, we first define a risky asset holding indicator. We classify households as risky asset holders if they hold any positive risky assets and as non-risky asset holders if they do not hold any. Though this definition does not distinguish stock holdings from mutual fund holdings, it is still a good approximation of household risky asset market participation. We then run the panel logit regression with the indicator of risky asset holders as a dependent variable. The results are shown in Column 1 of Table 3.4. As the table shows, households are more likely to invest in the stock market after retirement than before. This finding is statistically significant at the 1% level. By calculation, the marginal effect of retirement is 1.8 percent. Part of the retirement effect can be attributed to the fact that some households become risky asset investors after retirement.

To test the intensive margin, we first focus on households with only positive risky assets. The result, reported in Column 2 of Table 3.4, shows no significantly statistical difference. However, as we know, restricting our analysis to only a conditional sample may incur a sample selection problem. To deal with this issue, we further conduct the Heckman selection model under a panel data setting. The result, in Column 3 of Table 3.4 shows that after dealing with the sample selection issue, households increase risky shares by 1.7 percent after retirement, and this effect is statistically significant. This result indicates that the increase in the intensive margin also contributes to the retirement effect that we found in the benchmark results.

In short, we find that this retirement effect comes from both the extensive and intensive margins, but mostly from the extensive margin effect, i.e., retirees who refrained from buying risky assets before retirement tend to buy them after retirement. We do not try to decompose and quantify each effect in this paper, but this would be an interesting investigation for future studies.

Table 3.4: Extensive and Intensive Margin Analysis

	Panel Logit	Panel Conditional on Participation	Panel Conditional on Participation (Heckman Selection Model)
	(1)	(2)	(2)
Head Completely Retired	0.155***	0.006	0.017*
	[0.048]	[0.007]	[0.010]
Head Age	-0.106	-0.018***	-0.027***
	[0.000]	[0.006]	[0.008]
Head Age Square	0.001**	0.000	0.000*
	[0.000]	[0.000]	[0.000]
Head Self-Reported Health	-0.005	0.007	0.007
(1:Poor/Fair, 0:Excellent/VeryGood/Good)	[0.054]	[0.009]	[0.009]
Household Size	-0.085***	-0.001	-0.008
	[0.024]	[0.004]	[0.006]
Number of Children	0.169***	0.017**	0.030***
	[0.047]	[0.007]	[0.010]
ln(Household Income+1)	0.464***	-0.005	0.031
	[0.034]	[0.005]	[0.021]
ln(Household Wealth+1)	0.726***	0.014***	0.075**
	[0.031]	[0.005]	[0.034]
Change Marital Status	0.065	-0.028	-0.022
	[0.331]	[0.049]	[0.049]
Spouse Age	0.026		
	[0.039]		
Spouse Age Square	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Spouse Self-Reported Health	0.029	-0.007	-0.005
(1:Poor/Fair, 0:Excellent/VeryGood/Good)	[0.053]	[0.008]	[0.008]
Year Fixed Effect	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes
Observations	28851	23954	23954
Chi-square	1739.72		
Wald p-value	0.00		
R-squared		0.02	0.02
F-Statistics		11.73	11.36

Notes: The dependent variable for the Logit Regression is the probability of participating in the stock market. For the intensive margin analysis, the stock share conditional on stock market participation is used as a dependent variable. In the Logit Regression, samples with no within household variation are dropped (29,436 observations). Standard errors are in parentheses. All standard errors are clustered at the household level.

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

3.5 Possible Explanations for the Retirement Portfolio Choice Puzzle

The previous section established that there exists a sizable retirement effect on household's risky-asset investment. This result is very robust across different specifications and cannot be explained by existing theories. In this section, we further propose and test four possible explanations for this positive retirement effect. One caveat: these represent only four out of many possible explanations.[25]

3.5.1 Changes in Risk Tolerance

Many factors, such as age, wealth, health status, and working status, can affect risk tolerance. Now, provided that risk tolerance is positively correlated to risky asset holdings (Canner et al., 1997), when retirement itself increases risk tolerance, the increased risk tolerance boosts the chance that individuals will invest more in risky assets. More specifically, before retirement, individuals encounter many other uncertainties, including employment uncertainty, labor income uncertainty, and so forth. Given these uncertainties, individuals have lower risk tolerance and, thus, maintain fewer risky asset holdings. In contrast, after retirement, those work-related uncertainties disappear, prompting individuals to be more risk-tolerant and to invest more in risky assets.

To test this risk-tolerance hypothesis, we employ the risk-tolerance measure proposed by Barsky et al. (1997), which is constructed from a series of hypothetical questions on the comparison of a job with a fixed wage to jobs with wage uncertainties. This measure is constructed by two categorical variables: a categorical variable from 1 to 4, and a categorical variable from 1 to 6. Note that the larger the number, the more risk-tolerant the households. Since both measures are categorical variables, we consider both the ordered logit regression and the panel regression. The results of the ordered logit regression are reported in Columns

[25] For example, tax concerns might be another possible channel, which we do not discuss here due to a lack of data.

1 and 3, and the results of the panel regression are presented in Columns 2 and 4 in Table 3.5.[26] Across all specifications using different measures, we can observe that households have higher risk tolerance after retirement than before retirement, which is consistent with our conjecture above.

Although the cardinal proxy for risk tolerance provides evidence that the risk preference shifts after retirement, using this cardinal proxy to study household behavior raises issues, including measurement error problems (Kimball et al., 2008). To overcome these issues, Kimball et al. (2008) develop an imputation method. Following their methodology, we impute the relative risk-tolerance for retirees and non-retirees separately under the assumption that the risk preference would change after retirement. Table 3.6 shows the result of regressions of imputed risk-tolerance measures on retirement status. As the first and second columns of the table show, imputed risk-tolerance and log risk-tolerance measures become higher after retirement. Similarly, households have a lower risk-aversion coefficient after retirement. The results with imputed risk-tolerance measures also confirm that households become more risk-tolerant after retirement.

3.5.2 Time Spending

Next, we consider how the availability of more time, associated with retirement, might drive the retirement effect. As we know, individuals have more time after retirement for keeping track of risky asset markets, and they might even gain utility from trading risky assets. If this is the case, individuals would be likely to invest more in the risky assets once they have more time after retirement.

To test this hypothesis, we use one measure, "tracking the stock market," in HRS. This measure is drawn from the question: "How closely do you track the stock market: very

[26] Since 2000, the HRS has asked these income gamble questions of individuals under age 65. Thus, our samples contain only about 15% of respondents above 65 for the four-category risk measure, and 19% above 65 for the six-category risk measure. To deal with the possible bias caused by this sample selection, we conduct the same analysis using the subsample before survey year 2000. The result with the subsample, which is reported in Table A.10 in Appendix A.5, shows a similar pattern, although the statistical significance is reduced due to a substantial drop in the sample size.

Table 3.5: Channel Test

	Risk Tolerance				Following	Life Expectancy Living		Probability of Leaving Bequest		
	4 Cat.		6 Cat.		Stock Market	To Age 75	To Age 85	10K+	100K+	Any
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Head Completely Retired	0.205***	0.199***	0.115**	0.342***	0.277***	-0.008	-0.058***	-0.330	0.435	-1.336***
	[0.048]	[0.055]	[0.057]	[0.108]	[0.045]	[0.007]	[0.011]	[0.399]	[0.667]	[0.421]
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effect	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15904	15904	9954	9954	18576	36700	38215	56459	31016	31418
Pseudo R-square	0.01		0.01		0.07					
Chi-square	204.51		219.69		1271.08					
R-squared						0.04	0.05	0.01	0.02	0.02
F-Statistics						46.43	60.07	24.14	23.89	12.30

Notes: This table shows the result of testing 4 possible explanations for increasing risky share after retirement. As shown in the first row in the table, the dependent variables are the subjective risk tolerance measure, time allocation to stock market, self-reported life expectancy, and probability of leaving bequest, respectively. In the column (1), (3), and (5), the ordered logic regression is used. The panel regression is used in the other columns. Standard errors are in parentheses. All standard errors are clustered at the household level. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 3.6: Channel Test - Imputed Risk Tolerance Measure

	Risk Tolerance	Log Risk Tolerance	Risk Aversion
	(1)	(2)	(3)
Head Completely Retired	0.007**	0.030*	-0.206*
	[0.004]	[0.016]	[0.120]
Household Characteristics	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes
Observations	12770	12770	12770
R-square	0.02	0.02	0.02

Notes: As shown in the first row in the table, the dependent variables are the imputed risk tolerance measure, the imputed log risk tolerance measure, and the imputed risk aversion coefficient, respectively. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

closely, somewhat closely and never?" The value of this measure is assigned as 1, 2 or 3, respectively. The larger the number, the more closely the subject follows the stock market. We again use the ordered logit regression, and the results appear in Column 5 of Table 3.5. We find that retirement does increase the time spent of tracking the stock market, which supports the time-spending hypothesis.

3.5.3 Life Expectancy

As Cocco and Gomes (2012) suggest, individuals who have a longer life expectancy plan for a longer horizon and, accordingly, they will allocate more of their assets to saving, switching their portfolio towards a lower risk. If retirement changes an individual's perception about her life expectancy, then this could possibly affect her portfolio choice. It is possible that when an individual is working, she feels healthy and capable. Once retired, she may feel less healthy and less capable, thus reducing her anticipated life expectancy. This pessimistic view on life expectancy after retirement could lead to a decrease in savings and an increase in risky assets.

To determine whether the retirement effect could occur in response to changes in anticipated life expectancy, we examine whether retirement decreases anticipated life expectancy across different levels of optimism. Here, we use the self-reported probability of living to ages 75 and 85 to test this hypothesis. The results are given in Columns 6 and 7 of Table 3.5. As shown, on average, individuals tend to perceive a lower life expectancy after retirement. In particular, retirement decreases the individual's expectation of living to age 75 by 0.8 percent and of living to 85 by 5.4 percent. Such results support the conclusion that the retirement effect could be caused by a decrease in retirees' anticipated life expectancy, though not all of them are not all statistically significant.

3.5.4 Bequest Motives

We may also expect that retirement could weaken bequest motives, which, in turn, might increase the probability that households invest in more risky assets.[27] When individuals are employed, they may consider themselves to be in a better financial situation, giving them a stronger bequest motive. Once retired, individuals would experience a sudden loss of labor income and may view themselves as less capable than before. And this view of a weaker self may weaken the bequest motive. If this is the case, changes in bequest motives may be another possible explanation for the retirement effect.

In the HRS, bequest motives are measured using a sequence of questions. Individuals are first asked whether they intend to leave a bequest of $10K or more and the probability of doing so. If the probability of leaving a bequest of $10K is positive, then individuals are asked whether they intend to leave a bequest of $100K or above and the probability. However, if the probability of leaving a bequest of $10K is zero, individuals are asked whether they want to leave any bequest and with what probability. We treat each of these questions as a different measure of bequest motives. We regress these three measures of bequest motives

[27] Cocco et al. (2005) argue that people with stronger bequest motive draw down their wealth more slowly and this, in turn, results in a lower risky share.

on retirement. The results are shown in Columns 8 to 10 of Table 3.5. A relatively weaker bequest motive is found after retirement, though it is not statistically significant except for the question of leaving any. Although the evidence is relatively weak, these findings suggest that a weaker bequest motive is also a possible explanation for an increase in risky share holding after retirement.

3.6 Robustness

In this section, we present various robustness checks, including: 1) adopting an alternative risky share definition by incorporating IRA accounts; 2) using an alternative retirement status that classifies partial retirement as "retired"; 3) including both the household head's retirement status and the spouse's retirement status simultaneously; 4) excluding another possible explanation of market-driven passive asset holdings; 5) further exploring the potential non-linear effect of age, income, and wealth; 6) conducting a placebo test by artificially assigning a "forced retirement age;" 7)conducting additional analysis from PSID data; and 8) exploring heterogeneities regarding wealth, mortgage and pension.

3.6.1 Alternative Risky Share Definition

In the previous sections, we focused on the risky share measure defined by the ratio of risky assets (stocks and mutual funds) to total financial assets, where financial assets do not include retirement accounts. One may argue that when making portfolio decisions, individuals will not only take their non-retirement financial assets into account, but also consider their retirement accounts, in their total assets. To address this concern, we use an alternative risky share measure by including the IRA account and its respective portion in stocks. This new risky share measure is defined as (stocks + mutual funds + IRA stocks)/ (financial assets+IRA).[28] The new results are summarized in Table 3.7. It shows that the

[28]Since the HRS includes IRA account information only since 2000 and only precise asset allocation information from the 2006 wave samples, using the new risky share measure will make our sample size much smaller than under our original definition.

Table 3.7: Robustness - Alternative Risk Measure

	(1)	(2)
Head Completely Retired	0.063***	0.023**
	[0.006]	[0.010]
Household Characteristics	Yes	Yes
Head Characteristics	Yes	Yes
Spouse Characteristics	Yes	Yes
Year Fixed Effect	Yes	Yes
Household Fixed Effect	No	Yes
Observations	18459	18459
R-square	0.17	0.01
F-Statistics	239.65	11.30

Notes: The dependent variable is the stock share in financial and IRA assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

retirement effect persists and this effect is quantitatively similar to the results obtained using our initial risky share definition. In other words, our results are robust to risk portfolio measure both with and without including the retirement account.

3.6.2 Alternative Retirement Definition

In Section 4 and Section 5, we use self-reported retirement status and only treat individuals as retired only if they report "fully-retired." Although there is no formal verification of an individual's retirement status, there are a set of alternative measures that can be used for robustness checks. We will present the results with different retirement measures in Table 3.8. In Column 1, we use the same measure as in Sections 4 and 5. In Column 2, we define a new retirement status by including both fully-retired and partially-retired individuals as retirees. In Columns 3 and 4, we construct the retirement measures from a question about labor force participation. This question is: "What is your current labor force status: working, unemployed, not in labor market, disabled, partially retired, fully retired?". To define retirement status, we exclude individuals who are either "not in labor market" or "disabled" from our sample. Similar to the retirement definitions used in Columns 1 and 2, we classify

Table 3.8: Robustness - Alternative Definition of Retirement

	Self-Reported Retirement Status		Labor Force Status	
	Completely	Completely/Partially	Completely	Completely/Partially
	(1)	(2)	(3)	(4)
Head Retired	0.015***	0.013**	0.011**	0.013**
	[0.004]	[0.004]	[0.004]	[0.004]
Household Characteristics	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes
Observations	65750	65750	64636	64636
R-squared	0.02	0.02	0.02	0.02
F-Statistics	46.94	46.68	46.67	46.63

Notes: The dependent variable is the stock share in financial assets. In the first two columns, the retirement dummy is created using the self-reported retirement status. In the last two columns, the retirement dummy is created using the labor force status, and the unemployed and the disabled groups are excluded. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

an individual as a retiree if he reports labor force participation as "fully-retired." In Columns 3 and 4, we classify an individual as a retiree if he reports labor force participation as either "fully retired" or "partially retired." As shown in Table 3.8, the retirement effect is robust to different retirement status definitions.

3.6.3 Spouse's Retirement Status

Another concern about the retirement effect stems from the fact that men and women differ with respect to their risk aversion, which affects their investment decisions (Barber and Odean, 2001; Addoum, 2013). To address this concern, we estimate the retirement effect by including both male household heads' retirement status and their spouses' retirement status in our estimation equation at the same time. Table 3.9 shows that the positive retirement effect is driven only by the household head's retirement status. The spouse's retirement negatively contributes to portfolio choice, although the coefficients are not significant for all specifications.[29] These results indicate potential gender differences in portfolio choice during

[29] In the instrumental variable estimations, we construct the spouse's expected retirement status and age indicators as IVs for the spouse's retirement status, in the same spirit as instruments defined for the household

Table 3.9: Robustness - Retirement Status of Spouse

	Panel (1)	IV1 (2)	IV2 (3)	IV3 (4)
Head Completely Retired	0.017***	0.106**	0.059*	0.076*
	[0.005]	[0.046]	[0.031]	[0.041]
Spouse Completely Retired	0.003	-0.070	-0.059**	-0.052
	[0.004]	[0.055]	[0.029]	[0.044]
Household Characteristics	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes
Observations	52435	52435	47467	13472
Endogeneity Test Statistics		3.72	4.71	2.32

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

the transition into retirement, which was evaluated by Addoum (2013). However, our results based on unconditional samples are opposite to his results from samples with positive risky shares.

3.6.4 Passive Holdings

Passive holdings occur when the stock market crashes and stock prices decline sharply. In this scenario, individuals with stock holdings might be reluctant to sell their stocks at such low prices. When this happens at the same time as retirement, this confounding effect of passive holding might be misinterpreted as the retirement effect. To distinguish the retirement effect from the passive holding effect, we first control for the wave fixed-effects in our regression. Additionally, we conduct subsample regressions that drop the observation in the 2008 to 2010 waves to avoid the potential passive holding effect caused by the 2008-2009 crisis. These results, displayed in Table 3.10, do not show any significant difference from those obtained by using the full sample, which suggests that the retirement effect is not

head's retirement status.

Table 3.10: Robustness - Non Crisis Sample

	(1)	(2)
Head Completely Retired	0.015***	0.015***
	[0.004]	[0.004]
Household Characteristics	Yes	Yes
Head Characteristics	Yes	Yes
Spouse Characteristics	No	Yes
Year Fixed Effect	Yes	Yes
Household Fixed Effect	Yes	Yes
Observations	70588	54162
R-square	0.01	0.01
F-Statistics	50.73	36.08

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

driven by the crisis.[30]

3.6.5 High-Order Effects in Age, Income and Wealth

Age, income, and wealth may affect risky share holding nonlinearly. Though we control for age, income, and wealth in both linear and square terms, this might not be sufficient to capture the high-order effects, if any.[31] To explicitly exclude this possibility, we use different specifications to add further higher-order terms to our regression by using age, age square, age cubic and age quadratic terms, log of income, log income square, log of wealth and log wealth square. As shown in Table 3.11, after controlling these high-order terms, our retirement effect still persists.

[30] For the internet bubble crisis of early 2000, we also conduct a similar subsample test by restricting our sample up to the 2000 wave. The results are qualitatively similar.

[31] We also use specification with log terms.

Table 3.11: Robustness - Including High Order Terms

	(1)	(2)
Head Completely Retired	0.009***	0.010***
	[0.004]	[0.004]
Head Age	0.066	0.274
	[0.282]	[0.330]
Head Age^2	-0.002	-0.007
	[0.007]	[0.008]
Head Age^3	0.000	0.000
	[0.000]	[0.000]
Head Age^4	-0.000	-0.000
	[0.000]	[0.000]
ln(Household Income+1)	0.034***	0.027***
	[0.005]	[0.006]
ln(Household Income+1)^2	0.006***	0.001
	[0.002]	[0.002]
ln(Household Wealth+1)	0.048***	0.055***
	[0.002]	[0.002]
ln(Household Wealth+1)^2	0.004***	0.004***
	[0.000]	[0.000]
Household Characteristics	Yes	Yes
Head Characteristics	Yes	Yes
Spouse Characteristics	No	Yes
Year Fixed Effect	Yes	Yes
Household Fixed Effect	Yes	Yes
Observations	86276	65750
R-squared	0.03	0.03

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

3.6.6 Placebo Test

Since HRS data are constructed solely from self-reported answers to survey questions, there might be some reporting errors. More specifically, imagine that if individuals tend to misreport their retirement status, the retirement effect we obtained in the previous section could be driven by some unobserved factors that determine *reported* retirement status rather than *actual* retirement status. To address this issue, we conduct some placebo tests. We artificially set ”fixed” retirement ages, above which people will be labeled as ”retirees.” Under each specification, we set a fixed retirement age, ranging from 62 to 70 in Columns 1 through 9, respectively. If the retirement effect is not driven by other unobserved factors that may affect reported retirement status, we should not expect significant retirement effects from our placebo tests. The results are reported in Table 3.12. We find that this ”artificial” retirement is effective only when set at age 65, the minimum legal age for full retirement benefits, by which age the portion of retirees increases rapidly. The placebo tests in Table 14 indicate that our results are not driven by other potential factors and, thus, indirectly support our main findings of the retirement effect on the portfolio choice.

3.6.7 Results from PSID Data

To provide additional evidence, we also conduct a similar analysis for the benchmark case by using the Panel Study of Income Dynamics (PSID) database. Comparing to HRS, the main advantage of PSID is that it traces the life-time income dynamics thus covers younger respondents than HRS. It is possible to better capture the life-cycle dynamics of portfolio choice. On the other hand, the disadvantage is that it has less detailed information regarding retirement than HRS. Thus, we conduct analysis by using full samples (household heads aged from 30 to 80) and comparable samples to HRS (household heads aged from 50 to 80). The results are reported in Table 3.13. Columns 1 and 3 are results from pooled cross-sectional regression after controlling year dummies. Columns 2 and 4 are results from

Table 3.12: Placebo Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\boldsymbol{I}$(Age of Head $\geq$ 62)	0.004								
	[0.004]								
$\boldsymbol{I}$(Age of Head $\geq$ 63)		0.006							
		[0.004]							
$\boldsymbol{I}$(Age of Head $\geq$ 64)			0.005						
			[0.004]						
$\boldsymbol{I}$(Age of Head $\geq$ 65)				0.010**					
				[0.004]					
$\boldsymbol{I}$(Age of Head $\geq$ 66)					0.006				
					[0.004]				
$\boldsymbol{I}$(Age of Head $\geq$ 67)						0.004			
						[0.004]			
$\boldsymbol{I}$(Age of Head $\geq$ 68)							0.002		
							[0.005]		
$\boldsymbol{I}$(Age of Head $\geq$ 69)								-0.002	
								[0.005]	
$\boldsymbol{I}$(Age of Head $\geq$ 70)									-0.008
									[0.005]
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65750	65750	65750	65750	65750	65750	65750	65750	65750
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
F-Statistics	46.59	46.66	46.54	46.67	46.48	46.41	46.39	46.44	46.53

Notes: The dependent variable is the stock share in financial asset. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 3.13: Retirement Effect on Portfolio Choice by Using PSID Data

	30 to 80		50 to 80	
	OLS	Panel	OLS	Panel
Head Retired	0.029***	0.042***	0.028***	0.041*
	[0.005]	[0.016]	[0.006]	[0.021]
HH Wealth	0.003***	0.003***	0.003***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]
HH Income	0.007***	0.007***	0.005***	0.008***
	[0.000]	[0.001]	[0.000]	[0.002]
Age	-0.003***	-0.006**	-0.007*	-0.023*
	[0.001]	[0.003]	[0.004]	[0.014]
Age Squared	0.000***	0.000**	0.000*	0.000*
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.104***	0.183***	0.259**	0.715
	[0.019]	[0.067]	[0.128]	[0.435]
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	No	Yes	No	Yes
Observations	47144	47144	18364	18364
R-squared	0.19	0.19	0.20	0.22

Notes: The dependent variable is the stock share in financial asset. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

panel regression.[32] The results here are consistent with the main results based upon HRS data, though the magnitudes are slightly larger than those from HRS. In PSID samples, retirement increases risky shares by 2.8 percent to 4.1 percent, which is comparable to our main results.

3.6.8 Heterogeneities

We may expect the retirement effect to be heterogeneous across different characteristics. Here, we explore the potential heterogeneities regarding 1) wealth; 2) mortgage holding; and 3) pension holding.

[32]Since the IVs included in our main context cannot be fully constructed in PSID, we do not report the IV results by using age eligibility for retirement benefit here. The results are qualitatively similar, though.

3.6.8.1 Heterogeneities by Wealth

Among all possible characteristics, the retirement effect is more likely to be different across wealth levels. Intuitively speaking, individuals from households with a limited budget can allocate money only to support themselves, and may not be able to buy any risky assets. In light of this constraint, changes in portfolio choice are less likely to occur after retirement. In contrast, for individuals from wealthier households, who have more flexibility in allocating money towards different portfolio choices, changes in portfolio choice are more likely to occur after retirement. Taking this into account, we explore the possible heterogeneity across different wealth levels.

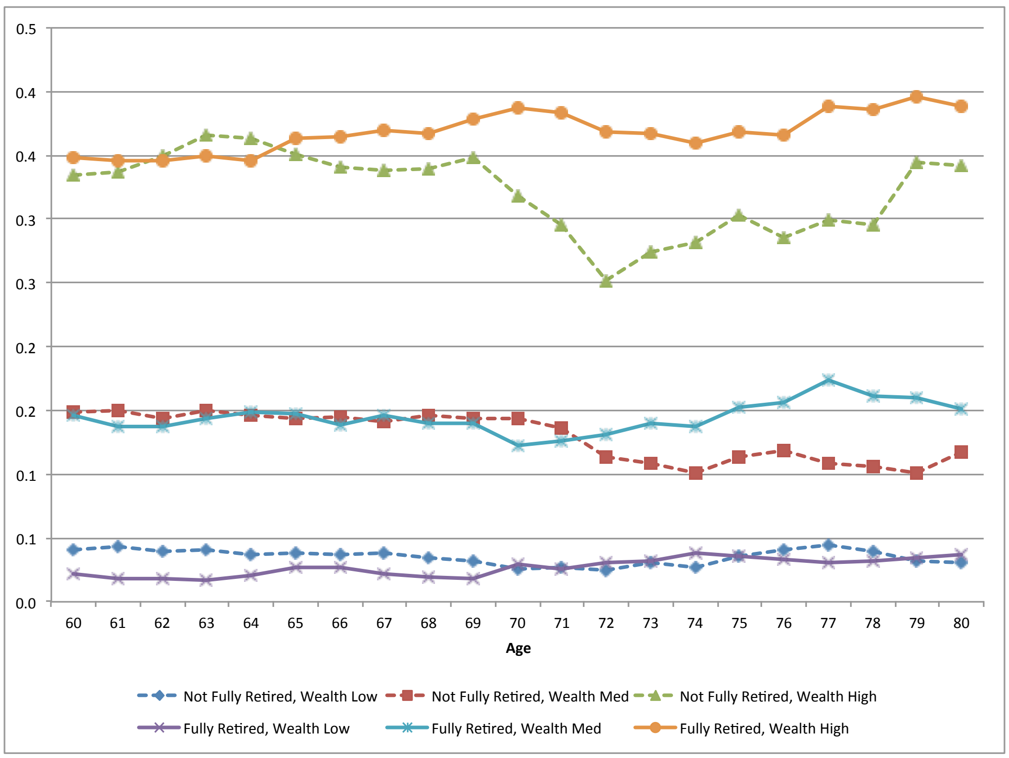
We split each wave sample evenly into three groups according to wealth: high, medium, and low. We first plot the average risky shares of the three groups in relation to retirement status across different ages. As illustrated in Figure 3.4, in the high-wealth group, retirees, in general, have larger risky share holdings than do non-retirees. For this group, the pattern is robust across different ages. The medium- and low-wealth groups, on the other hand, do not exhibit any substantial difference between retirees and non-retirees.

To examine the heterogeneity across wealth levels, we also conduct regression analyses, including both panel regression and IV panel regression, as before.[33] The results are summarized in Table 3.14. The low-wealth group is omitted as a reference group in all specifications. Column 1 provides the results in a simple panel regression. The result shows that the retirement effect can be attributed mainly to the high-wealth group, where the coefficient on the interaction term of the high-wealth group indicator and the retirement indicator is positive, although only the results in Columns 2 and 4 are statistically significant.

For the medium and low wealth groups, this retirement effect is not evident. The IV results in Columns 2 to 4 show that not only does the high-wealth group experience a jump in risky shares around retirement, but individuals from the medium-wealth group are also

[33] When we conduct an instrumental variables regression analysis for specifications with retirement-wealth interactions, we instrument these interactions by interactions between our instrumental variables and wealth indicators. Similar settings are adopted for other heterogeneity tests.

Figure 3.4: Risky Share by Age and Wealth Group



This graph is based on the aggregate samples in the HRS from the 1992 wave to the 2010 wave. The risky share is the share of total value of stock in financial assets. The wealth group is based on the total value of household assets, including financial assets and housing assets. To identify the retirement status, self-reported retirement status is used.

Table 3.14: Heterogeneity - Wealth

	Panel (1)	IV1 (2)	IV2 (3)	IV3 (4)
Head Completely Retired	0.008	0.016	0.056**	0.041
	[0.006]	[0.030]	[0.023]	[0.026]
Household Wealth High	0.108***	0.078***	0.105***	0.076***
	[0.006]	[0.011]	[0.008]	[0.011]
Household Wealth Medium	0.042***	0.021**	0.047***	0.022**
	[0.005]	[0.009]	[0.007]	[0.009]
Head Completely Retired × Wealth High	0.011	0.043**	0.005	0.038**
	[0.007]	[0.020]	[0.014]	[0.018]
Head Completely Retired × Wealth Medium	-0.005	0.024	-0.020	0.020
	[0.007]	[0.019]	[0.013]	[0.018]
Household Characteristics	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes
Observations	65750	27888	61930	27421
R-square	0.03	0.03	0.03	0.03
F-Statistics	64.47	34.51	61.74	33.62
Endogeneity Test Statistics		4.63	5.08	11.19
p-value		0.20	0.17	0.01

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

affected, though to a lesser degree. The low-wealth group experiences no significant effect on portfolio choice at retirement.[34]

3.6.8.2 Heterogeneity by Mortgage Holdings

As with wealth, the retirement effect is also likely to be heterogeneous in terms of mortgage holdings. The idea is that since mortgage holders need to pay back their mortgages

[34]These findings are consistent with our conjecture in the sense that individuals in the low-wealth group rarely hold risky assets either before or after retirement. In the data, the average risky holdings for the low wealth group are just 4.5%.

even after retirement, they 1) may not have enough money to invest in risky assets and 2) may not be willing to invest more in risky assets, which would mean bearing more risk. If this is the case, we expect that the retirement effect for mortgage holders will be smaller than that for non-mortgage holders.

Here, we consider two measures to examine the heterogeneous retirement effects. For the first measure, we classify households with any mortgage as mortgage holders and the rest as non-mortgage holders. We define this dummy variable as the first measure of mortgage holding. For the second measure, we use the natural log of mortgage reported in the HRS data as a continuous measure of mortgage holdings.

Table 3.15 provides the regression, similar to that in Table 3.14. Columns 1 to 4 report the results using the first measure and Columns 5 to 8 report the results using the second measure. As shown in Table 3.15, the coefficient of the interaction term between the mortgage dummy and the retirement status dummy is negative, though it is statistically significant only for non-IV specification. Based upon these coefficients, we calculate that the retirement effect on risky share holdings for non-mortgage holders is 1.4 percentage points higher in the panel regression and 0.8-2.2 percentage points higher in the IV setting than for mortgage holders. Similar patterns can be found by using the second measure.

3.6.8.3 Heterogeneity by Pension Holdings

Pension holdings are another factor that might lead to the heterogeneous retirement effect. The constant benefit flow from pensions could have different effects on the investment choices of pension holders and non-pension holders and, in turn, influence the retirement effect differently across the two groups.

Here, in order to examine the heterogeneity of retirement effect of pension holding, we consider one pension measure to classify households into pension holders and non-pension holders. More specifically, we classify households as pension holders if they report any

Table 3.15: Heterogeneity - Mortgage

	Panel	IV1	IV2	IV3	Panel	IV1	IV2	IV3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Head Fully Retired	0.020***	0.066***	0.050**	0.073***	0.024***	0.057**	0.059***	0.074***
	[0.004]	[0.022]	[0.020]	[0.019]	[0.005]	[0.025]	[0.022]	[0.022]
Head Fully Retired × Mortgage Holder	-0.014**	-0.022	-0.014	-0.008				
	[0.006]	[0.016]	[0.012]	[0.015]				
Mortgage Holder	0.009**	0.013*	0.012**	0.011				
	[0.004]	[0.007]	[0.006]	[0.007]				
Head Fully Retired × ln(Mortgage Value)					-0.002***	-0.004***	-0.002**	-0.003**
					[0.001]	[0.001]	[0.001]	[0.001]
ln(Mortgage Value)					0.001	0.002**	0.001**	0.002**
					[0.000]	[0.001]	[0.001]	[0.001]
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65308	27716	61476	27252	59191	24505	55227	24042
R-square	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
F-Statistics	46.87	29.30	44.70	28.69	44.92	28.23	42.73	27.55
Endogeneity Test Statistics		3.46	2.55	8.50		4.27	3.54	5.47
p-value		0.18	0.28	0.01		0.12	0.17	0.06

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 3.16: Heterogeneity - Pension

	Panel (1)	IV1 (2)	IV2 (3)	IV3 (4)
Head Completely Retired	0.011*	0.061*	0.083***	0.078***
	[0.007]	[0.034]	[0.029]	[0.030]
Head Completely Retired × Pension Holder	0.004	-0.007	-0.037**	-0.008
	[0.007]	[0.022]	[0.019]	[0.020]
Household Characteristics	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes
Observations	65750	27888	61930	27421
R-square	0.02	0.03	0.02	0.02
F-Statistics	49.64	30.79	47.65	30.28
Endogeneity Test Statistics		2.86	6.97	8.61
p-value		0.24	0.03	0.01

Notes: The dependent variable is the stock share in financial assets. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

type of patterned benefit and the rest as non-pension holders.[35] We interact the pension dummy with retirement status as an additional variable. Table 3.16 shows that there is no significant difference between pension holders and non-pension holders, except for the result in Column 3.[36] This indicates that differences in retirement income flows cannot explain the retirement effect. Ideally, we would also explore heterogeneity across different pension schemes. However, since there is limited information in HRS, we will leave this for future study.

[35]From our definition, the pension holder indicator is time invariant; thus, it is automatically omitted from our panel regression.
[36]This is also evidence that the retirement effect is not driven by differences in post-retirement income flows due to different retirement benefit schemes.

3.7 Conclusion

Our paper first explores the positive causal effect of retirement on risky asset holdings, after correcting for the endogeneity bias associated with retirement status. We find that retirement leads to approximately a 5.4-6.7 percentage point increase in the risky shares of households' portfolio holdings, accounting for approximately one fourth of the increase in risky asset holdings. In addition, from the estimation distinguishing retirement duration, we find that this increase occurs mainly immediately after retirement and then persists over time. These results support a positive increase pattern of risky asset holding over time, as predicted by a stream of theories, but are not consistent with the smoothed transition pattern that these theories suggest.[37]

Then, we further investigate the retirement effect on extensive margin versus intensive margin and find that it is mainly driven by the fact that households without risky assets start to hold risky assets after retirement. To better understand these patterns, we tentatively propose and test four possible hypotheses that could explain this sizable shift due to retirement. We show that this retirement effect can be associated with four possible scenarios: 1) higher risk tolerance; 2) more time to track risky asset markets; 3) perception of shorter life expectancy; and 4) lower bequest motive. The first two scenarios are stronger and more robust, but one caveat is that we cannot distinguish these scenarios simultaneously.

There are several possible directions that we will explore in future work. First, we will develop a sensible theoretical model that could reconcile such a large positive retirement effect. Second, as retirement is associated with decreased income risk, it is also worth discussing how the decrease in income risk affects portfolio choice. Third, we will try to find richer data that could allow us to distinguish the four channels proposed above simultaneously.

[37] This stream of literature includes Viceira (2001), Cocco et al. (2005), Gomes and Michaelides (2005) and Cocco and Gomes (2012).

APPENDICES

APPENDIX A

Appendices

A.1 Subprime Lending with Asymmetric Information

A.1.1 Model Setup

Instead of discussing the case in which borrowers' quality are continuous, in this section, I follow Rajan et al (2010), by assuming that there is a continuum of borrowers with two types of borrowers, $C \in \{C_h, C_l\}$, where $C_h > C_l$.[1] Each borrower has private information about its own type, but the bank and investors do not. The ex ante probability of a borrower with default costs, C_h, is q, which is common knowledge. Types are independent and identically distributed across borrowers.

At $t = 0$, a borrower applies for a mortgage loan valued at P_0. Following the same mortgage term as in the symmetric case, repayment $M = (1 + r)P_0$ is to be paid at $t = 1$. At date 0, the bank costlessly observes a hard information signal $x \in \{x_h, x_l\}$ about the borrower.[2] Based on this signal, the bank decides whether to obtain a soft information

[1] In their paper, the authors argue that the bank's screening incentive is negatively associated with this probability, a proxy for the bank's exposure to the securitization market, which is aligned with my intuition described in Section 1. In their model, the bank and investors have the same value for a given loan. I further introduce the value differences between the bank and the investors as in the symmetric model. In addition, I also explicitly introduce housing price expectations to analyze the interaction effect.

[2] The hard information signal is also observed by investors costlessly.

signal $y \in \{y_h, y_l\}$ by incurring a cost k. The soft information signal is not verifiable by a third party. Investors cannot learn whether the bank incurs k to obtain y. Using all available information, the bank decides whether to offer the borrower a mortgage and, if the bank does offer a mortgage, it sets the balance-due M.

As we know from the symmetric information case, the mortgage payment for high-quality borrower $M(C_h)$ is determined by

$$U^H = -\int_0^{M(C_h)-C_h} C_h f(P, \mu_P) dP + \int_{M(C_h)-C_h}^{\infty} (P - M(C_h)) f(P, \mu_P) dP = 0 \tag{A.1}$$

If $M(C_h)$ is offered to a low-quality borrower, she always accepts the offer because

$$\begin{aligned} & -\int_0^{M(C_h)-C_l} C_l f(P, \mu_P) dP + \int_{M(C_h)-C_l}^{\infty} (P - M(C_l)) f(P, \mu_P) dP \\ & > -\int_0^{M(C_h)-C_h} C_h f(P, \mu_P) dP + \int_{M(C_h)-C_h}^{\infty} (P - M(C_h)) f(P, \mu_P) dP \end{aligned} \tag{A.2}$$

Thus, any $M \leq M(C_h)$ will be accepted by both types of borowers, and any mortgage payment beyond $M(C_h)$ will be accepted only by the low-quality borrower. Therefore, the bank charges $M(C_h)$ for all the mortgage loans it issues.

Assume that lending at $M(C_h)$ is profitable for the bank only if the borrower is a high-quality one. Lending to a low-quality borrower with mortgage payment $M(C_h)$ causes a loss to the bank:

$$
\begin{aligned}
\pi_h^{OTH} &= -\eta(1+r_d)P_0 + \eta \int_0^{M(C_h)-C_l} Pf(P,\mu_P)dP + \eta \int_{M(C_h)-C_l}^{\infty} M(C_h)f(P,\mu_P)dP \\
&> 0 \\
&> -\eta(1+r_d)P_0 + \eta \int_0^{M(C_l)-C_l} Pf(P,\mu_P)dP + \eta \int_{M(C_l)-C_l}^{\infty} M(C_h)f(P,\mu_P)dP \\
&= \pi_l^{OTH} \qquad \text{(A.3)}
\end{aligned}
$$

Thus, the bank has an incentive to distinguish between borrowers of different types.

Assume that the hard information signal, x, and the soft information signal, y, are independent of each other. Both signals are informative: the posterior probability that the borrower has type C_h after observing x satisfies

$$\sigma_h = \Pr(C_h|x_h) = \frac{qs_h}{qs_h + (1-q)s_l} > q \qquad \text{(A.4)}$$

$$\sigma_l = \Pr(C_h|x_l) < 1-q \qquad \text{(A.5)}$$

where $s_i = \Pr(x = x_h|C_i)$ for $i \in \{h, l\}$, denoting the probability that the hard information is x_h given that the borrower's type is C_i.

Similar notations for the posterior probability that the borrower has type C_h after observing a soft information signal y are shown below:

$$\rho_h = \Pr(C_h|y_h) > q \qquad \text{(A.6)}$$

$$\rho_l = \Pr(C_h|y_l) < 1-q \qquad \text{(A.7)}$$

Given the signals (x_i, y_j), the posterior probability a borrower has type C_h is denoted

λ_{ij}. In particular,

$$\lambda_{lh} = \frac{\sigma_l \rho_h}{\sigma_l \rho_h + (1 - \sigma_l)\rho_l}$$

As in the general case discussed in the symmetric information case, assume that each loan has probability α of being sold through securitization to investors. and probability $1 - \alpha$ of being retained by the bank. For any loan made by the lender, investors observe the balance-due M on the hard information signal x. The soft information y is not verifiable and, thus, not contractible. Investors offer a price that equals their expected value of the loan. If investors believe that the borrower has type C_h with probability $b(x)$, the price of the loan offered by investors equals

$$P(x) = \eta(1 + r_d)P_0 + \pi_l^{OTD} + b(x)(\pi_h^{OTD} - \pi_l^{OTD})$$

As Rajan et al. (2010) point out, since all loans are offered at the same rate in equilibrium, acquiring soft information is valuable only if the pool of borrowers receiving the loans improves by doing so. The following assumptions guarantee that the bank retaining a loan will acquire soft information if the hard information signal is x_l.

Assumption 1:

$$\lambda_{ll} < -\frac{\pi_l^{OTH}}{\pi_h^{OTH} - \pi_l^{OTH}} < \lambda_{hl}$$

Assumption 2:

$$\frac{\sigma_l \rho_h}{\lambda_{lh}} A^{OTH} - k > B^{OTH}$$

Assumption 1 implies that the bank retaining a loan finds it optimal to screen out borrowers with signals (x_l, y_l) but not those with signals (x_h, y_l). Assumption 2 implies that a lender retaining a loan earns a higher profit from lending only to borrowers with signals (x_l, y_h) (i.e., as compared to lending to all borrowers with signal x_l. B^{OTH} and A^{OTH} are defined in the Proof of Lemma A.1.

A.1.2 Results

As in Rajan et al. (2010), the lender offers a loan to all borrowers who generate a hard information signal x_h, but may also choose to acquire a soft information signal on those with a hard information signal x_l. In equilibrium, the bank acquires soft information only if the degree of securitization is sufficiently low. When the lender acquires soft information, observing the signal y_l results in a denial of the mortgage application. These results are summarized in the following lemma.

Lemma A.1. *When Assumptions 1 and 2 hold, there exist securitization thresholds $\underline{\alpha}$, $\overline{\alpha} \in (0,1)$, with $\underline{\alpha} < \overline{\alpha}$, s.t. in equilibrium (1) a lender acquires soft information only if $\alpha < \underline{\alpha}$ and the hard information signal is x_l; and (2) a lender does not acquire soft information only if $\alpha > \overline{\alpha}$.*

Proof. In equilibrium, all loans are offered with mortgage payment $M(C_h)$, and all offers are accepted by the borrower, regardless of type. Soft information is valuable if the bank screens out borrowers with a soft information signal y_l. At the same time, the net gain from screening out borrowers with y_l exceeds the information acquisition cost k.

When the hard information signal is x_h,

$$\begin{aligned} P(x_h) &= \eta(1+r_d)P_0 + \pi_l^{OTD} + \sigma_h(\pi_h^{OTD} - \pi_l^{OTD}) \\ &> \eta(1+r_d)P_0 \end{aligned}$$

where π_l^{OTD} and π_h^{OTD} are the bank's expected profit by selling loans with C_l and C_h, respectively. The mortgage payment equals $M(C_h)$, which is determined in Equation (30). Thus, if it is sold to investors through securitization, the bank will get positive profit without acquiring the soft information. From assumption (1),

$$\pi_l^{OTH} + \lambda_{hl}(\pi_h^{OTH} - \pi_l^{OTH}) > 0$$

Even if the bank were to retain the loan, it would continue to lend to a borrower with a soft information signal y_l. Hence, the bank will offer loans to all borrowers with a hard information signal x_h without further acquiring the soft information signal y.

Next, suppose that x_l is observed, and investors believe that the bank screens these loans by the soft information signal y. That is, investors believe that the bank acquires soft information and offers loans only to those with y_h. In equilibrium, investors' beliefs must be consistent with the bank's optimal choice.

If the bank lends to borrowers with y_l, then if the loan is retained by the bank, by assumption (1),

$$\pi_l^{OTH} + \lambda_{ll}(\pi_h^{OTH} - \pi_l^{OTH}) < 0$$

Thus, it is not optimal for the bank to offer loans when y_l is further observed. Therefore, all loans being offered with x_l must generate y_h. Therefore,

$$P^S(x_l) = \eta(1 + r_d)P_0 + \pi_l^{OTD} + \lambda_{lh}(\pi_h^{OTD} - \pi_l^{OTD})$$

If the bank sells the loan, it obtains

$$\pi_l^{OTD} + \lambda_{lh}(\pi_h^{OTD} - \pi_l^{OTD}) - k$$

If it retains the loan, its payoff depends on the actual screening and lending strategies. If the bank acquires soft information and does not make loans to borrowers with y_l, then, its expected profit from a retained loan is

$$\pi_l^{OTH} + \lambda_{lh}(\pi_h^{OTH} - \pi_l^{OTH}) - k$$

The probability that a borrower with x_l will generate a soft information signal y_h equals $\sigma_l\rho_h + (1 - \sigma_l)\rho_l$, which can be written as $\frac{\sigma_l\rho_h}{\lambda_{lh}}$ since $\lambda_{lh} = \frac{\sigma_l\rho_h}{\sigma_l\rho_h+(1-\sigma_l)\rho_l}$. Then, the bank's expected payoff when it screens loans on soft information equals

$$\pi_{x_l}^{S} = \frac{\sigma_l \rho_h}{\lambda_{lh}} \{\alpha[\pi_l^{OTD} + \lambda_{lh}(\pi_h^{OTD} - \pi_l^{OTD})] + (1-\alpha)\,[\pi_l^{OTH} + \lambda_{lh}(\pi_h^{OTH} - \pi_l^{OTH})]\} - k$$

If the bank deviates and offers a loan to all borrowers with x_l without further acquiring y, for the part being sold through OTD, it gets price $P^S(x_l)$. Then its expected payoff is

$$\pi_{x_l}^{NS} = \alpha[\pi_l^{OTD} + \lambda_{lh}(\pi_h^{OTD} - \pi_l^{OTD})] + (1-\alpha)\,[\pi_l^{OTH} + \sigma_l(\pi_h^{OTH} - \pi_l^{OTH})]$$

The bank's best response is to screen on soft information if and only if

$$\pi_{x_l}^{S} \geq \pi_{x_l}^{NS}$$

Equivalently,

$$\alpha \leq \frac{\sigma_l \rho_h A^{OTH} - \lambda_{lh} k - \lambda_{lh} B^{OTH}}{\lambda_{lh}(A^{OTD} - B^{OTH}) - \sigma_l \rho_h (A^{OTD} - A^{OTH})}$$

where

$$\begin{aligned} A^{OTD} &= \pi_l^{OTD} + \lambda_{lh}(\pi_h^{OTD} - \pi_l^{OTD}) \\ A^{OTH} &= \pi_l^{OTH} + \lambda_{lh}(\pi_h^{OTH} - \pi_l^{OTH}) \\ B^{OTD} &= \pi_l^{OTD} + \sigma_l(\pi_h^{OTD} - \pi_l^{OTD}) \\ B^{OTH} &= \pi_l^{OTH} + \sigma_l(\pi_h^{OTH} - \pi_l^{OTH}) \end{aligned}$$

[3]

Define $\underline{\alpha} = \frac{\sigma_l \rho_h A^{OTH} - \lambda_{lh} k - \lambda_{lh} B^{OTH}}{\lambda_{lh}(A^{OTD} - B^{OTH}) - \sigma_l \rho_h (A^{OTD} - A^{OTH})}$; then, in equilibrium, the bank acquires soft information after observing a hard information signal x_l only if $\alpha \leq \underline{\alpha}$.[4] Assumption (2) $\lambda_{lh} B^{OTH} + \lambda_{lh} k - \sigma_l \rho_h A^{OTH} \geq 0$ ensures that $\underline{\alpha} \geq 0$.

[3] It is easy to verify that $A^{OTD} > B^{OTD}$ and $A^{OTH} > B^{OTH}$.

[4] It is immediate that when $\alpha = 1$, the payoff from screening on soft information is strictly lower.

Next, if the hard information signal is x_l, and investors believe that the bank does not screen on soft information, then,

$$P^{NS}(x_l) = \eta(1 + r_d)P_0 + \pi_l^{OTD} + \sigma_l(\pi_h^{OTD} - \pi_l^{OTD})$$

The bank's expected profit from selling the loan to investors equals

$$\pi_l^{OTD} + \sigma_l(\pi_h^{OTD} - \pi_l^{OTD})$$

If the loan is retained, the bank's expected profit is

$$\pi_l^{OTH} + \sigma_l(\pi_h^{OTH} - \pi_l^{OTH})$$

Then, analogous to the screening case above, the bank's expected profit without acquiring soft information is

$$\begin{aligned}
\widetilde{\pi}_{x_l}^{NS} &= \alpha[\pi_l^{OTD} + \sigma_l(\pi_h^{OTD} - \pi_l^{OTD})] + (1-\alpha)\left[\pi_l^{OTH} + \sigma_l(\pi_h^{OTH} - \pi_l^{OTH})\right] \\
&= \alpha B^{OTD} + (1-\alpha)B^{OTH}
\end{aligned}$$

If the bank deviates and screens on soft information, its expected profit turns out to be

$$\begin{aligned}
\widetilde{\pi}_{x_l}^{S} &= \frac{\sigma_l \rho_h}{\lambda_{lh}}\{\alpha[\pi_l^{OTD} + \sigma_l(\pi_h^{OTD} - \pi_l^{OTD})] + (1-\alpha)\left[\pi_l^{OTH} + \lambda_{lh}(\pi_h^{OTH} - \pi_l^{OTH})\right]\} - k \\
&= \frac{\sigma_l \rho_h}{\lambda_{lh}}\{\alpha B^{OTD} + (1-\alpha)A^{OTH}\} - k
\end{aligned}$$

Thus, it is optimal for the bank to not screen on soft information only if

$$\widetilde{\pi}_{x_l}^{NS} \geq \widetilde{\pi}_{x_l}^{S}$$

Equivalently,

$$\alpha \geq \frac{\sigma_l \rho_h A^{OTH} - \lambda_{lh} k - \lambda_{lh} B^{OTH}}{\lambda_{lh}(B^{OTD} - B^{OTH}) - \sigma_l \rho_h (B^{OTD} - A^{OTH})}$$

Define $\overline{\alpha} = \frac{\sigma_l \rho_h A^{OTH} - \lambda_{lh} k - \lambda_{lh} B^{OTH}}{\lambda_{lh}(B^{OTD} - B^{OTH}) - \sigma_l \rho_h (B^{OTD} - A^{OTH})}$; then, in equilibrium, the bank does not acquire soft information after observing a hard information signal x_l if $\alpha \geq \overline{\alpha}$.[5] Assumption (2) ensures that $\overline{\alpha} \geq 0$.

Since $A^{OTH} > B^{OTH}$ and $A^{OTD} > B^{OTD}$, we have

$$\lambda_{lh}(B^{OTD} - B^{OTH}) - \sigma_l \rho_h (B^{OTD} - A^{OTH}) < \lambda_{lh}(A^{OTD} - B^{OTH}) - \sigma_l \rho_h (A^{OTD} - A^{OTH})$$

Thus,

$$\overline{\alpha} > \underline{\alpha}$$

□

Lemma A.1 shares very similar features with Proposition 1 in Rajan et al. (2010) by pointing out that the bank's screening incentive is negatively associated with the degree of securitization. When the degree of securitization is low, the bank collects soft information when the hard information signal is x_l, and then the loan is priced accordingly. In contrast, when the degree of securitization is high, the moral hazard problem that affects the bank's incentive to collect soft information is too severe. In these circumstances, the bank obtains only hard information.

Note that these thresholds in Lemma A.1 depend on future housing price expectations. Next, I show how housing price expectations further alter the bank's screening incentive. Intuitively, when housing price expectations are higher, the loss caused by lending to a C_l borrower is lower because the borrower's default probability is smaller. Accordingly, the net benefit from acquiring soft information becomes smaller, while the screening cost k remains the same. Therefore, a higher housing expectation reduces the bank's screening incentive.

[5]It is immediate that when $\alpha = 1$, the payoff from screening on soft information is strictly lower.

When the bank sells loans through the securitization market to investors, both probability thresholds defined in Lemma A.1 decrease and the bank offers more loans to low-quality borrowers. Consequently, both ex ante lending and ex post default increase. These are the same predictions derived in the symmetric information case in Section 2. This result is formulated in the following Proposition.

Proposition A.2. *When Assumptions 1 and 2 hold, the threshold of securitization market exposures for the bank to further screen borrowers on soft information after observing* x_l*,* $\underline{\alpha}$*, decreases when housing price expectations increase. At the same time, the threshold of securitization market exposures for the bank to not screen borrowers,* $\overline{\alpha}$*, also decreases with higher housing price expectations.*

$$\frac{d\underline{\alpha}}{d\mu_P} < 0, \frac{d\overline{\alpha}}{d\mu_P} < 0$$

Proof. By taking the derivative with respect to μ_P. □

A.2 Replications of Purnanandam (2011)

Table A.1: Intensity of Mortgages Sold

	Model 1	Model 2	Model 3
preotd	0.501***		
	[9.06]		
premortgage	0.163		
	[0.55]		
after	0.018	0.030*	0.032**
	[0.26]	[1.95]	[2.14]
after*preotd	-0.191***	-0.180***	-0.184***
	[2.69]	[12.24]	[12.57]
after*premortgage	-0.025	0.002	-0.037
	[0.07]	[0.03]	[0.51]
logta	0.064***	-0.025	-0.001
	[4.09]	[0.70]	[0.03]
cil/ta	-0.466	-0.251	-0.317
	[1.58]	[0.92]	[1.17]
liquid	0.253	0.675***	0.428**
	[0.93]	[4.05]	[2.51]
absgap	-0.476***	0.230***	0.156*
	[2.87]	[2.75]	[1.86]
Observations	4055	4055	3958
R-Squared	0.19	0.97	0.97
State dummies	Yes	No	No
Bank fixed effect	No	Yes	Yes
Exclude large banks	No	Yes	Yes

The dependent variable, sold, measures bank i's mortgage sale as a fraction of its total mortgage loans at the beginning of quarter t. after is a dummy variable that equals zero for quarters before and including 2007Q1. Model 1 is estimated using the OLS method. Models 2 and 3 are estimated with bank fixed effects. Model 3 excludes banks with more than $10 billion in assets. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of the one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

Table A.2: Mortgages Defaults

	Model 1 Chargeoffs	Model 2 NPA	Model 3 Chargeoffs	Model 4 NPA
after	0.029***	0.318***	0.030***	0.325***
	[2.69]	[3.27]	[2.74]	[3.31]
after*preotd	0.067***	0.643***	0.068***	0.568***
	[6.44]	[6.77]	[6.43]	[5.98]
after*premortgage	-0.033	0.484	-0.037	0.148
	[0.65]	[1.04]	[0.71]	[0.31]
logta	0.04	0.663***	0.035	0.990***
	[1.54]	[2.81]	[1.30]	[4.16]
cil/ta	-0.01	0.665	-0.012	0.684
	[0.05]	[0.38]	[0.06]	[0.39]
liquid	0.258**	2.094*	0.285**	0.02
	[2.18]	[1.95]	[2.31]	[0.02]
absgap	-0.131**	-2.741***	-0.138**	-2.853***
	[2.20]	[5.09]	[2.27]	[5.26]
Observations	4056	4056	3958	3958
R-squared	0.46	0.7	0.46	0.71

This table provides the regression results of the bank fixed effects model. The dependent variable, default, is measured by either the mortgage chargeoffs or non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. after is a dummy variable that equals zero for quarters before and including 2007Q1. preotd is the average value of OTD mortgages to total mortgages during quarters 2006Q3, 2006Q4 and 2007Q1. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of the one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

Table A.3: Mortgage Defaults and Inability to Sell

	Model 1 Chargeoffs	Model 2 NPA	Model 3 Chargeoffs	Model 4 NPA
after	0.021**	0.239**	0.022**	0.264***
	[1.97]	[2.43]	[2.03]	[2.66]
after*stuck	0.082***	0.897***	0.085***	0.735***
	[6.13]	[7.23]	[6.21]	[5.91]
after*premortgage	-0.006	0.966**	-0.012	0.548
	[0.12]	[2.03]	[0.22]	[1.13]
logta	0.058**	0.578**	0.051*	0.927***
	[2.21]	[2.39]	[1.90]	[3.79]
cil/ta	-0.229	0.007	-0.236	0.172
	[1.17]	[0.00]	[1.19]	[0.10]
liquid	0.224*	2.074*	0.254**	-0.023
	[1.95]	[1.96]	[2.11]	[0.02]
absgap	-0.052	-2.256***	-0.058	-2.397***
	[0.89]	[4.18]	[0.96]	[4.40]
Observations	3740	3740	3642	3642
R-squared	0.47	0.71	0.47	0.72

This table provides the regression results of the bank fixed effects model. The dependent variable, default, is measured by either the mortgage chargeoffs or non-performing mortgages (scaled by the outstanding mortgage loans) of bank i during quarter t. after is a dummy variable that equals zero for quarters before and including 2007Q1. stuck measures the difference between loans originated before 2007Q1 and loans sold after this quarter. premortgage is the average ratio of mortgage assets to total assets for 2006Q3, 2006Q4 and 2007Q1. logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of the one-year maturity gap as a fraction of total assets. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

Table A.4: Future Housing Price Growth and OTD on Ex Ante Loan Risk for Year 2007

	Approval	LTI	Spread
fhgrowth	0.024***	-0.160***	-0.022
	[17.96]	[16.24]	[1.35]
otd	-0.094***	0.126***	0.084***
	[36.53]	[6.29]	[3.24]
otd*fhgrowth	0.018***	-0.002	0.025
	[11.66]	[0.19]	[1.59]
logta	-0.056***	-0.156***	0.022*
	[56.01]	[22.30]	[1.64]
cil/ta	-1.526***	-0.154*	0.692***
	[160.36]	[1.95]	[6.15]
liquid	0.282***	-0.648***	-0.356
	[16.84]	[5.71]	[1.49]
absgap	-0.047***	0.954***	0.775***
	[4.70]	[14.16]	[5.42]
Observations	222972	162638	25547
R-squared	0.19	0.01	0.01

This table provides the regression results of future housing price growth and bank's OTD on average riskiness for bank loans using a bank fixed effects model conducted at loan level. The dependent variables are 1) approval indicator; 2) loan-to-income ratio; and 3) interest spread. otd is the ratio of OTD mortgages to total mortgages. fhgrowth is the house price growth in the next year in the bank's primary market. loan amount is the amount of loan granted; logta measures the log of total assets; cil/ta is the ratio of commercial and industrial loans to total assets; liquid is the bank's liquid assets to total asset ratio; absgap is the absolute value of one-year maturity gap as a fraction of total assets; year 2008 is a year dummy variable. All continuous variables are winsored on both tails at the 1% level. * significant at 10%; ** significant at 5%; *** significant at 1%. Absolute value of t-statistics in brackets.

A.3 Endogenized Prices and the Issuer's Benefits

In this appendix, we will explicitly model the endogenous pricing rule from the zero expected profit conditions for competitive investors. Before doing so, we revise the model a bit to make the discussion easier. Instead of selling financial claims, we assume that there are two types of projects to be financed through debt. A good project has payoff R with probability 1, and a bad project has payoff R with probability p_B and zero payoff with probability $1 - p_B$. The cost of each project is 1. Again, assume that both projects are profitable with positive NPV i.e., $R > p_B R > 1$[6]. The timing is the same as that in the main discussion. When the project gets a good rating, its face value of debt is D_G; when the project gets a bad rating, its face value of debt is D_B. Then, the issuer's expected payoffs in three different cases can be written as $B = R - D_G$; $\Delta = p_B(R - D_G)$; $\delta = p_B(R - D_B)$. For a good project, it always succeeds and the issuer get the residual payment $B = R - D_G$. For a window-dressed bad project, it pays off only when it succeeds. The expected payoff to the issuer equals $\Delta = p_B(R - D_G)$ i.e., the project succeeds and pays the face value of a high-rated project. For a bad project being detected, it gets a low rating and the issuer's expected payoff is $\delta = p_B(R - D_B)$.

Now, new objective functions for the issuer and the CRA are

$$\max_q \lambda(R - D_G) + (1-\lambda)(1 - e^{-\frac{q}{1-\lambda}})e^{-t} p_B(R - D_G)$$
$$+(1-\lambda)[1 - (1 - e^{-\frac{q}{1-\lambda}})e^{-t}] p_B(R - D_B) - aq - f$$

$$\max_t f - bt - (1-\lambda)(1 - e^{-\frac{q}{1-\lambda}})e^{-t} L$$

At the same time, the prices for high-rated projects and low-rated projects are determined

[6] This assumption is not essential. Modeling bad projects with negative NPV does not qualitatively change the results.

by investors' IR constraints

$$\begin{aligned}
\lambda D_G + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}p_B D_G &\geq 1 \\
p_B D_B &\geq 1
\end{aligned}$$

The first IR constraint indicates that investors earn zero expected profit from investing in high-rated projects. The first term on the left-hand side is the expected gain from a good project, while the second term represents the expected gain from a window-dressed bad project. These two together must cover the investment cost 1. The second IR constraint indicates that investing in low-rated projects also pays back the investment cost.

The equilibrium can be characterized by the first-order conditions tegother with two binding IR constraints i.e.,

$$\begin{aligned}
e^{-\frac{q}{1-\lambda}}e^{-t}p_B(R-D_G) - e^{-\frac{q}{1-\lambda}}e^{-t}p_B(R-D_B) - a &= 0 \\
-b + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}L &= 0 \\
\lambda D_G + (1-\lambda)(1-e^{-\frac{q}{1-\lambda}})e^{-t}p_B D_G &= 1 \\
p_B D_B &= 1
\end{aligned}$$

Therefore, the equilibrium can be characterized by the following proposition.

Proposition A.3. *The interior equilibrium solution for the above game is*

$$\begin{aligned}
q^* &= (1-\lambda)\ln[1 + \frac{b}{(1-\lambda)L}\frac{1}{a}] \\
t^* &= -\ln[a + \frac{b}{(1-\lambda)L}] \\
D_G^* &= \frac{1}{\lambda + \frac{bp_B}{L}} \\
D_B^* &= \frac{1}{p_B}
\end{aligned}$$

Compared to the results discussed in the main context, the equilibrium efforts are with very similar expressions. The main comparative statics regarding economic fluctuations, λ, also holds.

Corollary A.4. *When prices are endogenously determined by investors' IR constraints,*

$$\frac{dq^*}{d\lambda} > 0, \; \frac{dt^*}{d\lambda} < 0$$

Proof. The result follows immediately by taking derivatives of q^* and t^* □

Therefore, endogenizing prices does not change the sign of the effect from economic fluctuations.

A.4 Institutional Background of Retirement Benefits

In the United States, various institutions have been developed to support retirees. In this Appendix, we document these institutions in detail. Understanding these institutions is important to our study because they may affect both retirement decisions and the financial decisions of retirees. Among various institutions for retirees, Social Security, Medicare, and Individual Retirement Accounts (IRA) are most influential.

Social Security is a federal insurance program for retirees. Based on the Social Security Act of 1935, Social Security has been developed into an Old Age, Survivors, and Disability Insurance (OASDI) program, which in 2013, provided benefits to about 88 percent of Americans aged 65 or above. Social Security, which is financed by a payroll tax, requires at least 40 quarters of working periods to be eligible for the retirement benefit. Before the 1983 Social Security Amendment, the full retirement age had been set at 65 for a long time. However, after the Amendment, the full retirement age gradually increased, depending on the year of birth, ranging from 65 to 67. Additionally, Social Security provides the option to claim a discounted retirement benefit before reaching the full retirement age. The earliest age to claim the benefit is 62, and the monthly benefit is discounted up to 30 percent. The option to postpone the benefit after reaching the full eligibility age is also available. In this case, the benefit increases up to eight percent yearly until age 70. According to the Social Security Administration's fiscal year 2013 Agency Financial Report, for 53 percent of married couples and 74 percent of unmarried individuals, the Social Security retirement benefit accounts for 50 percent or more of their income. Since many retirees rely on Social Security to finance their retirement, the eligibility age for the retirement benefit can be a key determinant of the retirement decision.

Social Security also provides Medicare, a health insurance program for those aged 65 and older. Medicare also is available for those with disabilities. As of 2013, the enrollment in the Medicare was about 51.9 million, and the elderly accounted for more than 83 percent of total enrollment. Even though it is not comprehensive in coverage, Medicare helps retirees pay for various medical services, including inpatient care in a hospital, doctors' services, and medications. In 2011, 89.9 percent of the elderly enrolled in Medicare, received some type of Medicare benefit. Since unexpected medical expenditures are among the most important concerns in retirement planning, the Medicare eligibility age is also important to the retirement decision.

The Social Security retirement benefit and Medicare cover the largest part of retirement expenditures. However, they cannot cover all of the expenditures for most retirees, who usually have some other types of income sources, such as pensions and savings. Additionally, the government provides tools for encouraging workers to save their earnings for retirement. The most well known way to save for retirement is the Individual Retirement Account (IRA) (or 401(k)). This retirement account provides the benefits of tax-free growth and deferred income tax. As workers save their earnings in this account, their earnings and profits from this investment are exempt from income tax until they withdraw them. However, once workers put their earnings in this retirement account, it is difficult to access this money without penalty until age 59.5, with certain exceptions: medical expenses, education expenses and first-time home purchase. Since the IRA takes a non-negligible portion of retirees' total assets, the age requirement for withdrawal can affect retirement decisions. Additionally, IRA accounts require retirees to withdraw a minimum amount of the fund after age 70.5; this is referred to as minimum required distributions (MRDs). As retirees pull out money from their IRA accounts, the money should go into one of their asset accounts or consumption. Therefore, this mandatory withdrawal requirement also can affect retirees' financial decisions.

A.5 Additional Tables

Table A.5: Sample Selection

Selection Criterion	Remaining Observations
Initial Sample	170,928
Excluding Self-Employment	157,516
Keep Household Head Aged from 50 to 80	121,639
Self-Reported Retirement Status is Known	99,087
Risky Share between 0 and 1	87,186

Table A.6: Summary Statistics

Variable	Mean	S.D.	Med	Min	Max
Retirement Status (Head)					
1:Completely Retired, 0:Partly Retired or Not Retired At All	0.461	0.499	0	0	1
1:Completely Retired or Partly Retired, 0:Not Retired At All	0.575	0.486	1	0	1
Retirement Status (Spouse)					
1:Completely Retired, 0:Partly Retired or Not Retired At All	0.436	0.496	0	0	1
1:Completely Retired or Partly Retired, 0:Not Retired At All	0.559	0.496	1	0	1
Age					
Head	64.6	7.97	64	50	80
Spouse	62.3	8.77	62	24	100
Size of Household	2.33	1.12	2.00	0	19.0
Number of Children	3.14	2.02	3.00	0	20.0
Race (Head)					
White	0.834	0.372	1	0	1
Black	0.128	0.335	0	0	1
Hispanic	0.067	0.250	0	0	1
Other Race	0.037	0.189	0	0	1
Level of Education (Head)					
Year of Schooling	12.9	3.04	12.0	0	17.0
High School	0.419	0.493	0	0	1
Some College	0.211	0.408	0	0	1
College and Above	0.255	0.436	0	0	1
Level of Education (Spouse)					
Year of Schooling	12.5	2.79	12.0	0	17.0
High School	0.414	0.493	0	0	1
Some College	0.232	0.422	0	0	1
College and Above	0.172	0.378	0	0	1
Self-Reported Health Status (Head)					
1: Poor or Fair, 0: Excellent, Vary Good, or Good	0.219	0.414	0	0	1
1: Poor, Fair, or Good, 0: Excellent, Vary Good, or Good	0.538	0.499	1	0	1
Self-Reported Health Status (Spouse)					
1: Poor or Fair, 0: Excellent, Vary Good, or Good	0.224	0.417	0	0	1
1: Poor, Fair, or Good, 0: Excellent, Vary Good, or Good	0.531	0.499	1	0	1
Medical Expenditure ($1,000)					
Head	1.79	2.26	1.07	0	12.0
Spouse	1.99	2.42	1.07	0	12.0
Wealth ($10,000)					
Total Asset	29.6	33.6	17.1	0	166
Total Asset Excluding 2nd Residence	28.3	31.7	16.5	0	155
Total Financial Asset	7.48	12.5	1.65	-0.86	59.9
Total Stock Asset	2.82	6.44	0	0	30.6
Income ($10,000)					
Total Income of Household	5.32	3.96	4.19	0.60	15.5
Total Income of Head	3.07	1.94	2.61	0	6.50
Total Income of Spouse	0.90	1.02	0.559	0	2.97
Risky Share					
Stock Share in Financial Asset	0.179	0.313	0	0	1
Stock Share in Financial and IRA Asset	0.232	0.337	0	0	1
Subjective Measure of Risk Tolerance					
1: Least Risk Averse; 4: Most Risk Averse	3.30	1.06	4	1	4
1: Least Risk Averse; 6: Most Risk Averse	4.66	1.51	5	1	6

Notes: All asset values are winsorized at the bottom 5 percent and top 5 percent level and deflated into 2000 Dollars.

Table A.7: Normal Retirement Age in the US

Cohorts: Birth Date	Normal Age of Retirement
Before 1/2/1938	65
1/2/1938-1/1/1939	65 and 2 months
1/2/1939-1/1/1940	65 and 4 months
1/2/1940-1/1/1941	65 and 6 months
1/2/1941-1/1/1942	65 and 8 months
1/2/1942-1/1/1943	65 and 10 months
1/2/1943-1/1/1955	66
1/2/1955-1/1/1956	66 and 2 months
1/2/1956-1/1/1957	66 and 4 months
1/2/1957-1/1/1958	66 and 6 months
1/2/1958-1/1/1959	66 and 8 months
1/2/1959-1/1/1960	66 and 10 months
1/2/1960 and later	67

Table A.8: First Stage Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Head Expected Retirement Status	0.238***	0.244***			0.177***	0.183***
	[0.008]	[0.009]			[0.009]	[0.010]
Partial Retirement Age			0.159***	0.166***	0.134***	0.136***
			[0.006]	[0.006]	[0.008]	[0.009]
Full Retirement Age			0.097***	0.088***	0.069***	0.067***
			[0.006]	[0.007]	[0.009]	[0.010]
Head Age	-0.028***	-0.026***	0.024***	0.027***	-0.053***	-0.054***
	[0.007]	[0.008]	[0.004]	[0.004]	[0.007]	[0.008]
Head Age Square	0.000***	0.000***	-0.000	-0.000	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Head Self-Reported Health	0.055***	0.068***	0.047***	0.053***	0.057***	0.069***
	[0.007]	[0.008]	[0.004]	[0.005]	[0.007]	[0.006]
Household Size	0.003	-0.000	-0.000	-0.003	0.003	-0.000
	[0.003]	[0.004]	[0.002]	[0.003]	[0.003]	[0.004]
Number of Children	0.004	0.006	-0.000	-0.003	0.004	0.006
	[0.005]	[0.006]	[0.003]	[0.004]	[0.005]	[0.006]
ln(Household Income+1)	-0.160***	-0.165***	-0.140***	-0.144***	-0.160***	-0.164***
	[0.005]	[0.006]	[0.003]	[0.004]	[0.005]	[0.006]
ln (Household Wealth+1)	0.007***	0.008***	0.004***	0.006***	0.007***	0.009***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]
Change Marital Status	-0.005	-0.027	-0.003	-0.042	-0.005	-0.030
	[0.016]	[0.056]	[0.010]	[0.035]	[0.016]	[0.056]
Spouse Age Square		-0.000		-0.000		-0.000
		[0.000]		[0.000]		[0.000]
Spouse Self-Reported Health		-0.021***		-0.014***		-0.023***
		[0.008]		[0.005]		[0.007]
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35960	28369	84978	64770	35348	27908
R-squared	0.45	0.44	0.32	0.31	0.46	0.45
F-Statistics	1102.70	693.82	762.98	463.24	1007.71	649.44

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.9: Tobit Regression

	Panel (3)	IV1 (4)	IV2 (5)	IV3 (6)
Head Completely Retired	0.054***	0.089	0.065	0.126**
	[0.008]	[0.056]	[0.052]	[0.051]
Head Age	-0.044***	-0.029*	-0.038***	-0.025
	[0.007]	[0.016]	[0.009]	[0.016]
Head Age Square	0.000***	0.000*	0.000***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Head Self-Reported Health	-0.048***	-0.038*	-0.077***	0.106***
(1:Poor/Fair, 0:Excellent/VaryGood/Good)	[0.009]	[0.020]	[0.013]	[0.020]
Household Size	-0.033***	-0.028***	-0.016***	-0.009***
	[0.004]	[0.007]	[0.005]	[0.007]
Number of Children	-0.009***	-0.018***	-0.005***	-0.004*
	[0.003]	[0.005]	[0.003]	[0.005]
ln(Household Income+1)	0.135***	0.148***	0.145***	0.154***
	[0.006]	[0.016]	[0.012]	[0.015]
ln (Household Wealth+1)	0.201***	0.274***	0.260***	0.272***
	[0.004]	[0.013]	[0.009]	[0.013]
Change Marital Status	0.026	0.147*	0.044	-0.006
	[0.054]	[0.083]	[0.062]	[0.083]
Spouse Age	0.001	0.001	-0.001	-0.000
	[0.005]	[0.010]	[0.006]	[0.010]
Spouse Age Square	0.000	0.000	0.000	-0.000*
	[0.000]	[0.000]	[0.000]	[0.000]
Spouse Self-Reported Health	-0.065***	-0.112***	-0.031***	-0.042***
(1:Poor/Fair, 0:Excellent/VaryGood/Good)	[0.009]	[0.019]	[0.011]	[0.019]
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	No	No	No	No
Observations	65750	28369	64770	27908
Chi-square	6675.84	2481.63	5644.98	2464.23
Wald p-value	0.00	0.00	0.00	0.00

Notes: In the Tobit regression, the zero stock share is cut off. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.10: Channel Test - Subject Risk Tolerance Measure with Subsample

	4 Cat.		6 Cat.	
	(1)	(2)	(3)	(4)
Head Completely Retired	0.265***	0.075	0.056	0.632*
	[0.067]	[0.138]	[0.114]	[0.361]
Household Characteristics	Yes	Yes	Yes	Yes
Head Characteristics	Yes	Yes	Yes	Yes
Spouse Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Household Fixed Effect	No	Yes	No	Yes
Observations	8432	8432	2506	2506
R-square		0.06		0.95
Chi-square	146.34		111.43	

Notes: This table shows the result of the ordered logic regression and panel regression of subjective risk measures on the retirement status. The subsample before year 2000 is used. Standard errors are in parentheses. All standard errors are clustered at the household level.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

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