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Essays on Debt in Macroeconomics

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Abstract

My dissertation consists of three chapters, where the common theme among them is debt and saving. My work contributes to our understanding of how debt markets function for entrepreneurs, large corporations and households.

The first chapter studies how entrepreneurs used personal borrowing to fund their businesses during the Great Recession. One of the defining characteristics of this period was a "credit crunch" during which the supply of credit dropped for all borrowers. I show that changes in the finances of entrepreneurs between 2007 and 2009 are consistent with entrepreneurs using personal assets to secure lending for their businesses and overcome this credit crunch. In particular, I find that home equity loan balances increased by 10%, despite a 12% drop in the value of aggregate housing stock. Entrepreneurs were responsible for 76% of the increase in home equity loan balances, while they only represent 13% of the population.

In the second chapter, I study the use of credit ratings by large corporations in the bond market. Over the last 25 years, there has been a drastic change in the distribution of corporate bond ratings: between 1985 and 2010 the number of firms issuing AAA or AA-rated debt dropped by 70%, while the number of firms issuing debt with lower ratings increased. I propose a mechanism whereby investors learn about firms through credit ratings and publicly available financial information and develop a model that incorporates this mechanism such that firms must devote resources to improving their rating. Under general conditions, the number of high-rated firms decreases in response to an increase in public signal accuracy.

The third chapter explores the role of financial market access on household consumption inequality. The standard macroeconomic models of consumption and saving with stochastic income processes have failed to match the rise in consumption inequality between 1980 and 2004. I present a model with idiosyncratic earnings risk and endogenous market segmentation between incomplete and complete markets for financial assets. This model improves upon the qualitative predictions regarding between-group and within-group consumption inequality of a standard incomplete markets model and a standard complete markets model with limited commitment.

Keywords: Macroeconomics, debt, entrepreneurs, credit ratings, bonds, inequality

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My doctorate could not have been completed without the support of many people. First and foremost, I'd like to express my most sincere thanks to my supervisor, Igor Livshits. I am very grateful for the countless hours he spent discussing my ideas and work, many of which were outside of typical working hours. My thesis was completed while I was a part-time student living and working abroad, an arrangement which required Igor's flexibility and patience.

Jim MacGee, a member of my committee, spent many hours reading and editing drafts of my work and presentations. My writing and presentation skills improved greatly under his guidance. His knowledge was invaluable and he was always willing to discuss ideas either in his office or over beers at the Grad Club.

I'd also like to thank the members of the macroeconomics group and other faculty members in the economics department. Feedback from these groups was always insightful and made me a better economist and researcher. No punches were pulled, and though this made presentations daunting, I came out better for it.

My fondest memories come from working and socializing with my fellow students. I learned a great deal from many of them and would not have completed my doctorate without their contribution. Completing course work and studying for core exams would have been unbearable alone. My favourite aspect of graduate school was the discussions about ideas, both important and inane, with intelligent, enthusiastic and knowledgeable people.

Finally, I would like to thank my family and friends for all of their support and encouragement. Most importantly, my wife Amanda showed a tremendous amount of patience over the final few years as I finished my thesis at night and on weekends while working during the day. It was difficult to remain motivated as I began my career but her gentle, and sometimes not so gentle, encouragement kept me on track. Other family members, including my mother, father, grandfather and aunt also helped a great deal simply by maintaining interest.

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Philadelphia, Pennsylvania

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Chapter 1

Introduction

My dissertation consists of three chapters, where the common theme among them is debt and saving. Each is a study of a different sphere of the economy: entrepreneurs, large corporations and households. My work contributes to our understanding of how debt markets function for each of these three groups.

The first chapter studies how entrepreneurs used their personal assets to fund their business during the financial crisis. I use panel data with rich information on household finances to show that entrpereneurs' reliance on home equity loans increased during the financial crisis. I further show that homeownership and borrowing against home equity increase the probability of survival. Though entrepreneurs were able to use home equity loans to survive the Great Recession, it was not costless since the increase in home equity borrowing exposed more household wealth to business risk at the height of the recession. Considering the influence entrepreneurs have on growth and employment (see, for example, Adelino, Schoar, & Severino, 2012), policies that ease borrowing constraints for entrepreneurs could potentially improve aggregate conditions during periods of tightened credit conditions.

The second chapter studies the use of credit ratings by large corporations in the bond market. I find that the virtual disappearance of firms with the highest credit ratings since 1985 was caused by increased dissemination and reliability of public information on firms brought about by the digital age. This lowers the value of credit ratings as "calling cards" of a firm's overall quality, as high credit ratings are costly to attain, and disseminating public information is not. Understanding how firms use credit ratings is important as regulation of the credit rating agencies has become a pressing policy issue following the financial crisis of 2007-2009.

The third chapter explores the role of financial market access on household consumption inequality. I present a model with endogenous segmentation in the market for financial assets. Restricted access to complete markets, which allow for full consumption insurance, captures the well-documented rise in consumption inequality between 1980 and 2004, which standard macroeconomic models of consumption and saving have failed to match. It is important to study economic inequality as it bears directly on policy concerns such as education and social security. Most of the existing literature has focused on the inequality of income or wealth. This is surprising as consumption, not income or wealth, is included in the household objective function and thus it should be of primary concern.

Chapter 2: Entrepreneurs' Use of Home Equity Loans During Credit Crises

One of the defining characteristics of the Great Recession was a credit crunch. The supply of credit dropped for all borrowers: individuals, corporations, small businesses and even governments. Many have argued (e.g. Duygan-Bump et al. [2010], and Ivashina & Scharfstein [2010]) that the supply of credit was especially limited during this period for businesses. In particular, for small businesses this credit crunch manifested itself in two ways: (1) small business loans made by commercial banks declined and (2) banks tightened lending standards for small businesses. As evidence, Duygan-Bump et al. (2010) document that small business loans made by commercial banks declined by $40 billion between June, 2008 and March, 2010, and, according to the Senior Loan Officer Opinion Survey on Bank Lending Practices, there were 13 consecutive quarters of tightening lending standards to small businesses.[1] These changes likely resulted in decreased investment, smaller payrolls and a decrease in the net rate of firm creation.

Without the ability to borrow, entrepreneurs would find it difficult to operate their businesses effectively and, in the worst cases, survive. Similarly, potential entrepreneurs would have difficulty starting a new business. As business lending dries up, entrepreneurs that are able to borrow using personal assets as collateral would be able to alleviate the pressures of a credit crunch. I show that changes in the finances of entrepreneurs between 2007 and 2009 are consistent with entrepreneurs using personal assets to secure lending for their businesses. In particular, I find that home equity loan balances increased by 10% ($73 billion), despite the large reduction in house prices that was a hallmark of the Great Recession.[2] Furthermore, during this period total consumer debt dropped slightly, suggesting that home equity loans were not simply another channel through which to borrow during a period of economic turmoil.[3] Interestingly, entrepreneurs were disproportionately responsible for 76% ($56 billion) of the increase in home equity loan balances, while they only represent 13% of the population. All told, entrepreneurs held 33% of aggregate home equity loan balances in 2007 and held 41% in

[1] More specifically, the first fact is a measure of the impact of the fall in supply, while the second is a measure of a tightening supply curve itself.

[2] After reaching its peak in 2007, by 2009 the value of aggregate housing stock had dropped by 12%.

[3] Knotek II & Braxton (2012) document a decrease in total consumer debt in every quarter but one since 2009.

2009, a large change in the distribution of this debt considering the short horizon. I argue that entrepreneurs used personal loans to supplement business loans, and thus increased borrowing against home equity is evidence of tighter credit constraints for entrepreneurs.

Not all entrepreneurs could borrow against their home equity, but those that could were able to mitigate the effects of the credit crunch. In support of this, I find that the entrepreneurs that survived had more personal assets in the form of home equity than those that exited.[4] Specifically, entrepreneurs that exited in 2009 had lower rates of homeownership and less home equity than surviving entrepreneurs during the crisis, suggesting that personal assets had an important effect on the ability to survive during the Great Recession. Surviving entrepreneurs had on average 62% more home equity and 51% more valuable homes than did exiters. Furthermore, homeowners were less likely to exit: of 2007 entrepreneurs, by 2009 18% of homeowners had exited, as opposed to 28% of non-homeowners. Surviving entrepreneurs increased borrowing against the value of their homes, whereas it decreased for exiters, an indication that entrepreneurs used home equity loans to finance their business. Also, the frequency of home equity loan use increased for survivors, but decreased for exiters. This leads me to conclude 2007 entrepreneurs substituted private lending, in the form of home equity loans, for business lending during the credit crisis.

Another manifestation of this phenomena is that entrepreneurs that started during the looser credit conditions of 2007 needed less home equity than those that entered during the credit crunch in 2009, a change in the pool of new entrepreneurs.[5] I compare entrants in 2007 before the crisis and entrants during the crisis in 2009. To consistently identify entrants in 2007 and 2009, I supplement the SCF panel with the typical SCF cross-section in 2007, which has more detailed data on respondents' businesses. I then classify an entrepreneur as new if they entered entrepreneurship in the two years preceding their interview. Reflecting tightened credit standards in 2009, 2007 entrants had less valuable homes (20%) and less home equity (63%) than 2009 entrants. As such, 2009 entrants had more housing wealth, *despite house prices falling.* This housing wealth was also more readily accessible to 2009 entrants: the number of entrants with an established home equity line of credit (HELOC) was two and a half times larger and limits increased by 17%. These findings are robust to controlling for the size of the business, as

[4]As is well documented, most recently by Wolff (2010), the home is typically a household's most valuable asset. As such, it is the primary source for collateral against personal loans, and so I focus on this asset in my analysis. In the SCF, averaging over all households, house value was 42% of total household assets in 2007 and 43% in 2009.

[5]Buera, Kaboski & Shin (2011) show that financial frictions account for a substantial fraction of the differences in cross-country TFP. Many studies, such as Hseih & Klenow (2009) and Banerjee & Duflo (2005), suggest that total potential TFP losses due to input misallocation are large. However, Midrigan & Xu (2013) find that financial frictions distort the entry decision for firms and that this channel, as opposed to the misallocation of capital, is responsible for the majority of the financial-friction induced differences in cross-country TFP.

measured by both the number of employees and business value using a probit model. Given the results for incumbent entrepreneurs, one might expect the homeownership rate for new entrepreneurs to be higher in 2009 during the crisis than in 2007 after the crisis, as tightened credit standards could preclude non-homeowners, more than homeowners, from starting a business. In fact, the homeownership rate is roughly constant over these two years. Though the proportion of homeowners and non-homeowners didn't change, non-homeowners seemingly were affected by the credit crisis, as the value of businesses started by non-homeowners in 2009 was drastically smaller than those started in 2007 by the same group.

To study how entrepreneurs used personal assets during the credit crunch, I employ the 2007-2009 panel edition of the *Survey of Consumer Finances*. This unique dataset is ideal for such a study as 2007 respondents were re-interviewed in 2009, and so it details the finances of households before and during the crisis. Furthermore, respondents are asked directly if they "actively manage" any owned business, which is how I define entrepreneurship.[6] The *SCF* also over-samples rich households, which include a large share of entrepreneurs,[7] and provides rich micro-data on household assets, debts and incomes.

Respondents in this data are not asked to specify the intended use of funds.[8] So, though the results suggest that entrepreneurs are using increased borrowing to fund their businesses, I do not directly observe that this is the case. Other studies, such as Herkenhoff, Phillips & Cohen-Cole (2016) and Adelino, Schoar & Severino (2013) also suffer from this limitation and reach similar conclusions, namely that observed changes in borrowing patterns imply that borrowing was used for business purposes. More directly, Robb & Robinson (2012) study the Kauffman Survey and determine that personal borrowing is an important source of start-up funding for many entrepreneurs.

Chapter 3: The Role of Public Information and Credit Ratings in the Corporate Bond Market

Firms with AAA credit ratings are disappearing. While in 1985 there were 34 firms with a AAA rating, by 2011 there were only 4.[9] The decline in top rated debt has also taken place at the AA level; between 1985 and 2010 the number of firms issuing AAA or AA debt dropped by 70%, while the number of firms issuing A or BBB debt increased by 77% and those issuing

[6] In most surveys, respondents are asked if they are self-employed or own a business and so cannot distinguish between the two. An example of this is the *Current Population Survey*.

[7] The correlation between wealth and entrepreneurship is documented in Gentry & Hubbard (2004), for instance.

[8] The SCF does ask if the respondent has used personal guarantees or collateral to secure business financing, though responses are not tied to any specific debt.

[9] The four firms, as rated by Standard & Poor's, are Johnson & Johnson, Automatic Data Processing Inc., Microsoft Corp. and Exxon Mobil Corp.

speculative grade debt increased by 129%. Overall the number of firms with a bond rating increased by 59%.

Why is the ratings distribution shifting towards more mediocre ratings? The answer to this question is important as bonds are now a larger share of corporate liabilities. In the Federal Reserve Board Flow of Funds Data, the share of total liabilities held in bonds grew by 26.5% between 1985 and 2010. Corporations are increasingly choosing bond and equity financing over other securities and bank financing.[10] Furthermore, the size the corporate bond market is massive; nonfinancial corporations had $4,691 billion of outstanding bond debt in 2010.[11] Considering the size and growth of this market, the underlying cause of the ratings shift may have a substantial effect on capital markets.

Credit ratings are ostensibly used by investors to determine how likely a firm is to default on its outstanding debt. Firms with AAA credit ratings are less likely to default than those rated AA, A, and so forth. On top of this, credit ratings are also a signal of the firm's general competence, as it is very difficult to achieve the highest ratings. As these ratings are useful to investors, firms will consult with ratings agencies prior to selling their debt.[12]

In part, the need for credit ratings is regulatory: many large, institutional investors are required to hold only investment grade bonds (BBB or higher). Additionally, it is difficult for firms to credibly relay this information directly to investors, and the auditing process would be very onerous for an individual investor. Thus the credit rating agencies are able to exploit some efficiencies of scale. There is a trade-off for firms however: they must devote resources to non-productive ratings activities in order to satisfy the requirements of the credit rating agencies, on top of the fee for the rating service itself.[13] For instance, a firm is required to hold cash on hand to satisfy the requirements for a particular rating. If credit ratings were not required to sell corporate bonds, firms might be able to reallocate their resources to increase profits.

Considering the value of a credit rating, a natural question arises: why are the highly rated firms disappearing? I argue that firms are no longer willing to pay the cost to achieve high ratings. To this point:

> "Scores of big companies have lost their AAA status in recent years as it became seen in board rooms as more of a straitjacket than a path to riches."
>
> (Eric Dash, New York Times, August 2, 2011)

To capture this change, I propose the following mechanism. As credit ratings have value as

[10] The change in share of total corporate liabilities was 20.7%, -76.7%, and -67.1% for equity, securities and bank financing, respectively.

[11] $7,167 billion outstanding at the end of 2016, per the most recent data available.

[12] Though it is possible to issue debt without consulting with a credit ratings agency, almost all firms do. Nevertheless, both Standard & Poor's and Moody's will issue a rating regardless of the firm's participation.

[13] This is typically a percentage of the size of the bond issue.

a signal of firm "quality" in the sense that they provide investors with information about the future performance of the firm, they are an alternative to other publicly available channels of firm information. These channels include SEC 10K filings, which contain pertinent financial data from public firms and are now provided electronically, as well as media such as the Wall Street Journal Online and Bloomberg. With the proliferation of this information, investors now have direct access to firm information which may convince them to purchase lower-rated bonds. Firms no longer need to rely solely on a credit rating as a signal of their type, as the demand for their bonds is now also dependent on this costless, public channel.

The topic was originally discussed in the financial press, from whom multiple answers emerged. Besides firms' unwillingness to pay for improved ratings, other suggestions include investors having a larger appetite for risk so they are more willing to purchase lower rated bonds, and investors no longer placing much stock in corporate bond ratings. Though seemingly disparate, I argue that these three answers are essentially the same. Firms will lower their rating and reduce the associated costs if they are able to sell their debt at a lower rating. This would be possible if the demand for lower investment grade bonds has increased relative to high investment grade bonds. In effect, there is lower demand for top ratings from both investors *and* firms.

To formalize this story, I construct a model that contains a "peacock" problem: the firm must divert resources to non-productive rating activities in order to improve its expected credit rating. Firms are endowed with a project and differ only in the probability that this project will pay off with the higher return. Both the credit rating and a costless public signal are correlated with the firm's type. This type is unknown to everyone, including the firm. As the firm learns something about its type from the public signal, this will influence the decision to invest in the rating process. Once this decision is made, a credit rating is formed. Knowing the public signal and the credit rating, investors then decide whether to invest in the firm's project. To capture the proliferation of information over the period in question, I increase the correlation of the public signal with a firm's type (the "accuracy" of the signal). Under general conditions, the resulting change in the distribution of credit ratings matches the change observed in the data.

The mechanism works as follows. Investors are unable to observe an individual firm's type but have access to credit ratings and the public signal. Firms with projects that have a higher expected payoff will be more likely to receive a high public signal and more likely to earn a high rating. The investors are then able to offer lower interest rates to those firms with higher ratings and signals. Additionally, a higher rating will increase the probability that a firm receives an investment. As the accuracy of the signal increases, firms and investors learn more about the type of the firm, which may induce firms to forego investing to achieve a high rating. In equilibrium, an increase in the accuracy of the public signal will result in fewer firms with high ratings and more firms with mediocre and low ratings.

The primary testable implication of the model is the increase in the dispersion of interest rates within a rating class. When the accuracy of the public signal is low, the interest rates given to two firms with the same rating and different signals will be closer than when the accuracy is high. In effect, the difference between interest rates increases with the accuracy of the signal as investors are more sure that these firms have different underlying types. Using data from the *Mergent Fixed Income Securities Database*, I show that this pattern is borne out between 1990 and 2010.

In all markets, the rating system is designed to measure relative credit risk. The credit rating agencies (CRAs) assert that a rating does not measure absolute default probability and that a rating does not constitute investment advice. The purpose of this position is to ensure protection from liability claims and to continue their status as a Nationally Recognized Statistical Rating Organization (NRSRO). This designation is important as only ratings from such an organization may be used to satisfy legal obligations as to which debt may be held by large, institutional investors. An example of such an investor is a pension fund which is required to hold only investment grade debt.[14] Another example is any bank that has committed itself to the Basel Accords, which specify a capital requirement based on the rating composition of the bank's assets.

Chapter 4: Consumption Insurance with Endogenously Segmented Markets

The household consumption-savings decision and consumption inequality have been important areas of research in economics, but some aspects remain unexplored to their full extent. In particular, I focus on the different level of access that households have to financial markets, the effect this has on household savings and investment, and what this means for consumption inequality. In this paper, differential access is caused by costs which are not proportional to income and thus cause heterogeneous behaviour across income levels. The motivation for this study comes from, in part, the empirical rejection of perfect risk sharing, i.e., that households are able to insure against all idiosyncratic shocks.[15] By adding a fixed cost for market participation, I show that the model exhibits the desired degree of risk sharing by controlling access on the *extensive* margin, while allowing income-rich households full consumption insurance. This further restricts the degree of risk sharing relative to the debt constraint models (discussed below) on an aggregate level. From a theoretical standpoint, the benefit of this fixed cost is that

[14] Debt is considered investment grade if it has a rating of BBB or above. Debt rated BB or lower is deemed speculative grade or high yield.

[15] See, for example, Attanasio & Davis (1996) who show that the standard Arrow-Debreu complete markets model cannot explain the joint distribution of earnings and consumption in U.S. cross-sectional data.

the market segmentation is *endogenous* and thus households can pay for access at any point in their lifetime.

The model of Endogenously Segmented Markets (ESM) developed herein exhibits a mixture of perfect risk sharing and no risk sharing in different segments of the economy. In order to justify such a model, there should be evidence of two features: heterogeneous market participation and a fixed cost for access. The former can be seen in the high concentration of asset holdings and wealth in the upper portion of the income distribution. Wolff (2010) finds that the top quintile by income holds 44% of their net worth in real estate, business equity, stock and bonds compared to 14% for the middle 3 quintiles in the *Survey of Consumer Finances* (SCF) in 2007. Furthermore, the author finds that 55% of the total value of life insurance is held by the top 10%. Studying the same sample, Guvenen (2007a) finds that 90% of non-housing wealth and 98% of stocks are owned by the richest 20% of the U.S. population by income. By most measures, the distribution of assets is heavily skewed to the left.

A fixed cost for access is not so easily observed. Following Guvenen (2007a), it is meant to capture both implicit and explicit costs endured by those who trade in financial markets. These would include time and effort costs of tasks that include filing a more complicated tax return, membership or access costs to internet trading houses, brokerage fees that aren't "per trade" and costs of information acquisition. Vissing-Jørgensen (2002) finds that modest costs ($50 to $260) are enough to explain the decision of most non-participants in the stock market.

The basic models on household consumption and savings fall into two classes. The first are the incomplete market models such as Aiyagari (1994) or Huggett (1993) in which infinitely-lived households use "precautionary savings" to smooth their consumption. More recently, Storesletten, Telmer & Yaron (2004) use the same framework in a life-cycle model. Though this market structure is useful as a lower bound for the asset set of an entire economy, there are clearly more opportunities to smooth consumption (such as disability insurance and other financial instruments). Saving with a single bond is arguably a more apt description of low-income household behaviour, as this group rarely holds their wealth in assets other than their primary residence. This can be seen in the SCF where households with income under $15,000 in 2007 make up 13.3% of households but hold only 1.2% of total stock holdings, either indirectly or directly. In the *Panel Study of Income Dynamics* (PSID), the asset income of households that earn more than $30,000 is over three times that of those that earn less than $30,000. The second class of models, such as the model studied in Kehoe & Levine (1993), restrict asset purchases in a more natural manner: debt constraints. In these models a household (or an agent) cannot commit to paying back any amount of debt which would make autarky more appealing, though they have access to assets which span the state space. In this sense, risk sharing is restricted on the intensive margin, i.e., households cannot borrow or lend as much as they wish but may purchase assets for every state.[16]

Krueger & Perri (2006) determine that the degree of risk sharing in the economy would seem to be in between that of a simple bond economy (incomplete markets) and an economy with limited commitment (restricted complete markets). The authors come to this conclusion as the increase in consumption variance from 1980 to 2004, as measured in the *Consumer Expenditure Survey* (CEX), is lower than that predicted by a bond economy and higher than that predicted by a debt-constrained economy.[17] It may be, however, that each of the basic models accurately describes a certain *segment* of the economy, while inaccurately describing the economy as a whole. As mentioned above, the single bond economy seems to suitably describe the behaviour of low-income households, while the observed wealth holdings of high-income households indicates that they have access to a wider class of assets.

It is important to study economic inequality as it bears directly on policy concerns such as education and social security. Most of the existing literature has focused on the inequality of income or wealth and ignored, to a certain degree, the inequality of consumption. This is surprising as consumption, not income or wealth, is included in the household objective function and thus it should be of primary concern. A recent paper by Heathcoate, Perri & Violante (2010) documents the economic inequality in the United States by examining changes in the variance of wages, hours worked, income, earnings and consumption. The authors find that the increase in consumption inequality is less than that of income inequality and suggest that this implies some part of the income process is insurable, but not all.[18] This is only true if, in response to rising income variance, all households behave in a similar fashion which I argue is not the case. The main result of this paper is that the observed increase in consumption inequality misrepresents the true welfare effect of an increase in income variance. This is because the increase in income variance has two effects on the unconditional variance of log consumption: (1) an increase in group risk sharing for high income households (as group market participation increases), resulting in lower consumption variance; and (2) a direct increase in consumption variance for low income households, as the fixed cost is more restrictive and market participation does not increase.

To further develop the ESM model, I examine the effects of a change in the persistence of income shocks. An increase in persistence will decrease the risk faced by a household, as it is subject to fewer shocks but will also increase the difference in lifetime utility caused by a high

[16]Kocherlakota (1996) shows that complete risk sharing is in fact possible in this environment if agents are sufficiently patient.

[17]I refer to the within-group (log of) consumption variance. The between-group variance is lower in the data than both of the basic models. The within-group variance is of more interest as it reflects the level of risk sharing in the economy.

[18]The authors also confirm that the samples used by the PSID, CEX and CPS are comparable, lending justification to the use of income and consumption data from the different surveys in the same study.

or low income shock. The model predicts a decrease in market participation when persistence is raised, suggesting that in this environment the former effect is more important for household welfare. Finally, I show that when the financial markets are interpreted as traditional insurance markets (such as for disability or life insurance), the ESM model supports two empirical observations which are seemingly opposed: namely, the negative correlation between *income* and insurance purchases and the positive correlation between *wealth* and insurance purchases. The intuition is that wealth is used for precautionary savings which become redundant for households that can afford the fixed cost of market participation.

Chapter 2

Entrepreneurs' Use of Home Equity Loans During the Great Recession

2.1 Introduction

One of the defining characteristics of the Great Recession was a credit crunch. The supply of credit dropped for all borrowers: individuals, corporations, small businesses and even governments. Many have argued (e.g. Duygan-Bump et al. [2010], and Ivashina & Scharfstein [2010]) that the supply of credit was especially limited during this period for businesses. In particular, for small businesses this credit crunch manifested itself in two ways: (1) small business loans made by commercial banks declined and (2) banks tightened lending standards for small businesses. As evidence, Duygan-Bump et al. (2010) document that small business loans made by commercial banks declined by $40 billion between June, 2008 and March, 2010, and, according to the Senior Loan Officer Opinion Survey on Bank Lending Practices, there were 13 consecutive quarters of tightening lending standards to small businesses.[1] These changes likely resulted in decreased investment, smaller payrolls and a decrease in the net rate of firm creation.

Without the ability to borrow, entrepreneurs would find it difficult to operate their businesses effectively and, in the worst cases, survive. Similarly, potential entrepreneurs would have difficulty starting a new business. As business lending dries up, entrepreneurs that are able to borrow using personal assets as collateral would be able to alleviate the pressures of a credit crunch. I show that changes in the finances of entrepreneurs between 2007 and 2009 are consistent with entrepreneurs using personal assets to secure lending for their businesses. In particular, I find that home equity loan balances increased by 10% ($73 billion), despite the

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large reduction in house prices that was a hallmark of the Great Recession.[2] Furthermore, during this period total consumer debt dropped slightly, suggesting that home equity loans were not simply another channel through which to borrow during a period of economic turmoil.[3] Interestingly, entrepreneurs were disproportionately responsible for 76% ($56 billion) of the increase in home equity loan balances, while they only represent 13% of the population. All told, entrepreneurs held 33% of aggregate home equity loan balances in 2007 and held 41% in 2009, a large change in the distribution of this debt considering the short horizon. I argue that entrepreneurs used personal loans to supplement business loans, and thus increased borrowing against home equity is evidence of tighter credit constraints for entrepreneurs.

Not all entrepreneurs could borrow against their home equity, but those that could were able to mitigate the effects of the credit crunch. In support of this, I find that the entrepreneurs that survived had more personal assets in the form of home equity than those that exited.[4] Specifically, entrepreneurs that exited in 2009 had lower rates of homeownership and less home equity than surviving entrepreneurs during the crisis, suggesting that personal assets had an important effect on the ability to survive during the Great Recession. Surviving entrepreneurs had on average 62% more home equity and 51% more valuable homes than did exiters. Furthermore, homeowners were less likely to exit: of 2007 entrepreneurs, by 2009 18% of homeowners had exited, as opposed to 28% of non-homeowners. Surviving entrepreneurs increased borrowing against the value of their homes, whereas it decreased for exiters, an indication that entrepreneurs used home equity loans to finance their business. Also, the frequency of home equity loan use increased for survivors, but decreased for exiters. This leads me to conclude 2007 entrepreneurs substituted private lending, in the form of home equity loans, for business lending during the credit crisis.

Another manifestation of this phenomena is that entrepreneurs that started during the looser credit conditions of 2007 needed less home equity than those that entered during the credit crunch in 2009, a change in the pool of new entrepreneurs.[5] I compare entrants in 2007 before the crisis and entrants during the crisis in 2009. To consistently identify entrants in 2007 and 2009, I supplement the SCF panel with the typical SCF cross-section in 2007, which has more

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[5]Buera, Kaboski & Shin (2011) show that financial frictions account for a substantial fraction of the differences in cross-country TFP. Many studies, such as Hseih & Klenow (2009) and Banerjee & Duflo (2005), suggest that total potential TFP losses due to input misallocation are large. However, Midrigan & Xu (2013) find that financial frictions distort the entry decision for firms and that this channel, as opposed to the misallocation of capital, is responsible for the majority of the financial-friction induced differences in cross-country TFP.

detailed data on respondents' businesses. I then classify an entrepreneur as new if they entered entrepreneurship in the two years preceding their interview. Reflecting tightened credit standards in 2009, 2007 entrants had less valuable homes (20%) and less home equity (63%) than 2009 entrants. As such, 2009 entrants had more housing wealth, *despite house prices falling.* This housing wealth was also more readily accessible to 2009 entrants: the number of entrants with an established home equity line of credit (HELOC) was two and a half times larger and limits increased by 17%. These findings are robust to controlling for the size of the business, as measured by both the number of employees and business value using a probit model. Given the results for incumbent entrepreneurs, one might expect the homeownership rate for new entrepreneurs to be higher in 2009 during the crisis than in 2007 after the crisis, as tightened credit standards could preclude non-homeowners, more than homeowners, from starting a business. In fact, the homeownership rate is roughly constant over these two years. Though the proportion of homeowners and non-homeowners didn't change, non-homeowners seemingly were affected by the credit crisis, as the value of businesses started by non-homeowners in 2009 was drastically smaller than those started in 2007 by the same group.

To study how entrepreneurs used personal assets during the credit crunch, I employ the 2007-2009 panel edition of the *Survey of Consumer Finances*. This unique dataset is ideal for such a study as 2007 respondents were re-interviewed in 2009, and so it details the finances of households before and during the crisis. Furthermore, respondents are asked directly if they "actively manage" any owned business, which is how I define entrepreneurship.[6] The *SCF* also over-samples rich households, which include a large share of entrepreneurs,[7] and provides rich micro-data on household assets, debts and incomes.

Respondents in this data are not asked to specify the intended use of funds.[8] So, though the results suggest that entrepreneurs are using increased borrowing to fund their businesses, I do not directly observe that this is the case. Other studies, such as Herkenhoff, Phillips & Cohen-Cole (2016) and Adelino, Schoar & Severino (2013) also suffer from this limitation and reach similar conclusions, namely that observed changes in borrowing patterns imply that borrowing was used for business purposes. More directly, Robb & Robinson (2012) study the Kauffman Survey and determine that personal borrowing is an important source of start-up funding for many entrepreneurs.

The study of financial constraints as they relate to entrepreneurship goes back at least to

[6]In most surveys, respondents are asked if they are self-employed or own a business and so cannot distinguish between the two. An example of this is the *Current Population Survey*.

[7]The correlation between wealth and entrepreneurship is documented in Gentry & Hubbard (2004), for instance.

[8]The SCF does ask if the respondent has used personal guarantees or collateral to secure business financing, though responses are not tied to any specific debt.

Evans & Jovanovic (1989), who studied a model of entrepreneurial entry and investment with collateral constraints.[9] As wealthy individuals are less likely to be constrained, they are more likely to become entrepreneurs *if financing constraints bind.* This implication is supported empirically by studies such as Gentry & Hubbard (2004), who find entrepreneurs own a substantial fraction of aggregate wealth. More recently, Schmalz, Sraer & Thesmar (2017) show that collateral constraints restrict firm entry and lower growth thereafter.[10] However, Hurst & Lusardi (2004) find that this relationship is non-linear as the entrepreneurship rate is flat up to the 80th percentile of wealth but increasing thereafter.[11] This finding has been challenged recently in studies such as Fairley & Krashinsky (2012), who find evidence of financing constraints for new entrepreneurs throughout the wealth distribution. In this paper, I find evidence of binding financing constraints for new and incumbent entrepreneurs.

Though the literature has focused on entrants, an exception is Cagetti & De Nardi (2006), who study a model where entrepreneurs choose entry, exit and investment. They find that borrowing constraints affect not only the entry and exit decisions, but also firm size and investment. In particular, tighter borrowing constraints lower the fraction of entrepreneurs and reduce average firm size. Buera (2009) also considers both the intensive and extensive margins and finds that the welfare costs of financing constraints are primarily caused by underinvestment in realized projects as opposed to forgoing potentially profitable projects.

Financing for entrepreneurs can be divided into two categories: (1) traditional business loans, from banks or other sources, and perhaps secured with assets owned by the business or future sales, for instance; and (2) personal loans through which entrepreneurs fund the business directly or obtain outside financing for the business by pledging personal assets as a guarantee.[12] Personal loans are an important source of credit for entrepreneurs in regards to both the amount of credit and the terms of borrowing. Avery, Bostic & Samolyk (1998) find evidence that most (55.5%) small business credit is backed by some form of personal guarantee or collateral. Berger & Udell (1995) find that riskier businesses are more likely to pledge personal collateral, and in doing so are able to obtain lower interest rates. The focus of this paper, home equity loans, should be considered as personal loans, as the equity in the entrepreneur's home is being pledged as collateral. I find the use of personal loans for business financing increased during the credit crunch.

[9] See Kerr & Nanda (2009) for a thorough survey.

[10] The authors study French administrative data and exploit collateral shocks in regional housing markets. They find that those who experience a positive house-value shock show a higher rate of entry and, upon entry, use more debt and have larger firms.

[11] This finding is supported by Moore (2004) who uses home equity at the time of entry as a proxy for wealth.

[12] Mankart & Rodano (2012) show that almost all entrepreneurial borrowing is secured and that this allows bankruptcy laws to be more lenient. See Berger & Udell (1998) for a thorough overview of small business finance.

All else being equal, an entrepreneur would prefer to use business loans, as personal loans increase the household's exposure to business risk, undoing the insurance against such risk provided by limited liability and personal bankruptcy exemptions.[13] The potential increase in business risk is significant as entrepreneurs hold a substantial fraction of wealth in their business: Moskowitz & Vissing-Jørgensen (2002) find that on average, entrepreneurs hold 70% of their equity in a single business. Furthermore, although entrepreneurs are, to varying degrees, exposed to undiversified business risk, Vereschagina & Hopenhayn (2009) find no evidence of a premium for entrepreneurial investment as compensation. In a model of occupational choice where wealthy households choose to become entrepreneurs, borrowing constraints induce relatively poor entrepreneurs to take on riskier projects, which leave them more susceptible to failure. That wealthier entrepreneurs fare better is supported by Levine & Rubinstein (2013), who find that, although median earnings for entrepreneurs are lower than non-entrepreneurs, median earnings of *incorporated* entrepreneurs are higher than median earnings of less-wealthy, unincorporated entrepreneurs.[14] Because the credit crunch limited the supply of small business credit, entrepreneurs faced the trade-off between obtaining credit through personal loans and increasing business risk exposure more frequently during this episode. Considering this, the period studied in this paper (2007-2009) is ideal.

As a home is typically a household's most valuable asset, there have been many studies into the effects of house value on small businesses. For instance, Adelino, Schoar & Severino (2013) exploited geographic variation to show that, between 2002-2007, areas with rising house prices experienced a higher rate of small business formation and that this was a significant source of employment.[15] The relationship between house values and the rate of entry into entrepreneurship during the Great Recession is less clear. Using micro-data, I find that the rate of entry increased between 2007 and 2009 for both homeowners and non-homeowners. This is surprising as I find evidence of increased use of home-equity-backed personal financing by entrepreneurs, and so one might expect the rate of entry for non-homeowners to *decrease* as they have no housing wealth. To this point, the housing wealth of entrants increased: entrants who were also homeowners had much more home equity in 2009 than in 2007. (Mean: 67%, median: 53%).[16] The increase in the entry rate (for both homeowners and non-homeowners) was

[13]Glover & Short (2010) show that incorporated entrepreneurs, i.e. those that benefit from limited liability, own larger, more productive businesses. Akyol & Athreya (2011) study a model of self-employment with bankruptcy exemptions and find that exemptions affect the rate and timing of entrepreneurship.

[14]Poschke (2012) studies a different source of entrepreneur heterogeneity, ability (as measured by level of education) and finds that both low and high ability people become entrepreneurs but not those of intermediate ability.

[15]In the UK, Black, de Meza & Jeffreys (1996) also use geographic variation to show increasing house values lead to increased entrepreneur starts.

[16]Unfortunately, information on the location of respondents is not available in the SCF. Thus I am unable to directly address the impact of geographic variation in this paper.

most likely caused by depressed labour markets, as Fairley (2013) also finds that the entrepreneurship rate increased in 2009, more so in areas with high local unemployment. In contrast, Schott (2013) uses MSA-level macro-data and finds the number of start-ups decreased over the same period, and that this was caused by lower home equity. Seemingly, the Great Recession affected the entrepreneurship rate through two opposing channels. First, a credit crunch and lower house prices changed the conditions for business financing, thereby altering the pool of entrants. Second, poor labour market options induced more households to enter entrepreneurship. The focus of this paper is the personal financing channel, though I will present some evidence for the second channel as well.

The paper proceeds as follows. In Section 2.2, I describe the data and discuss why my definition of entrepreneurs is appropriate and then present summary statistics in Section 2.3. In the following two sections I first investigate incumbent and then new entrepreneurs to shed light on the net flow of entrepreneurs during the financial crisis. In Section 2.4, I show how home equity and the use of home equity loans affected incumbent entrepreneurs by documenting differences in the finances of exiting and surviving entrepreneurs, in particular the change in the exit rate. In Section 2.5, I do the same for new entrepreneurs in 2009 by comparing them to new entrepreneurs in 2007. I conclude in Section 2.6.

2.2 Data

I begin by describing the dataset used herein and then defining entrepreneurship within the context of this study. I then offer some basic facts concerning the households defined as entrepreneurs.

The *Survey of Consumer Finances* (SCF) is a tri-annual survey of households that contains in-depth data about a household's finances. The survey is a combination of two sub-samples: a standard sample and an over-sample of rich households. This feature is important for this project as the majority of entrepreneurs are wealthy and having additional observations in the upper-tail of the wealth distribution allows for stronger inferences about entrepreneurs. Another benefit of the SCF is a large and comprehensive series of questions concerning business ownership. These questions allow me to distinguish between households that own a business and those that not only own the business, but also "actively manage" said business. I use the following questions to define an entrepreneur:[17]

1. Do you (or your family living here) own or share ownership in any privately-held businesses, including farms, professional practices, limited partnerships or other business

[17]These are questions X/P3103 and X/P3104 in the 2007-2009 SCF.

investments that are not publicly traded?

2. Do you (or anyone in your family living here) have an active management role in any of these businesses?

If a household answers "yes" to both questions, I call this household an entrepreneur.

Why is this the appropriate definition of an entrepreneur? I am interested in determining whether household assets, specifically the home, eased financing constraints for those who run a business. There are two aspects to such households: business ownership and responsibility for financing decisions. Ownership and active management jointly convey that the household fulfills both of these features. Those households who report being self-employed and do not own a business make no financial investment and so are never constrained in their ability to finance a business, independent of credit conditions. Business owners who do not actively manage their business are passive investors and do not partake in the financing decisions of the firm.

As can be seen in Figure 2.1, the vast majority of business owners ("Business Owner") also actively manage their business ("Active Business Owner"). However, though the fraction of households that report being self-employed ("Self-Employed") is similar to the fraction that report being active business owners, the intersection of these two groups ("Active and Self-Employed") reveals that these definitions are not identical (and that any differences are consistent across survey years.) Thus, in order to study households that both own and financially operate a business, an actively-managed business owner is the appropriate definition of an entrepreneur.

The panel edition of the SCF was commissioned by the Federal Reserve Board in response to the Great Recession.[18] Fortunately, interviewers had access to the 2007 responses concerning actively managed businesses, ensuring accuracy in this regard. The re-interview had an 89% response rate with little variation in the response rate across demographics between 2007 and 2009. As discussed in Kinneckell (2010), the survey weights were adjusted to account for these changes.

To deal with missing data in the survey, the SCF uses multiple imputation. The dataset has five entries for each observation, one of which is the true observation and four of which are replicates. Though the imputation procedure is mean-preserving, the replication adds unwarranted observations. So as not to report standard errors which are too high, I drop the replicates when comparing moments across sub-samples, as is standard in the literature.[19]

[18] This was not the first panel edition attempted with the SCF. The 1986 survey respondents were re-interviewed in 1989, but issues arose which called the survey weights into question. See Freis, Starr-McCluer & Sundén (1998) for discussion.

[19] See Kinnickell (2011) for a discussion on weights in the SCF.

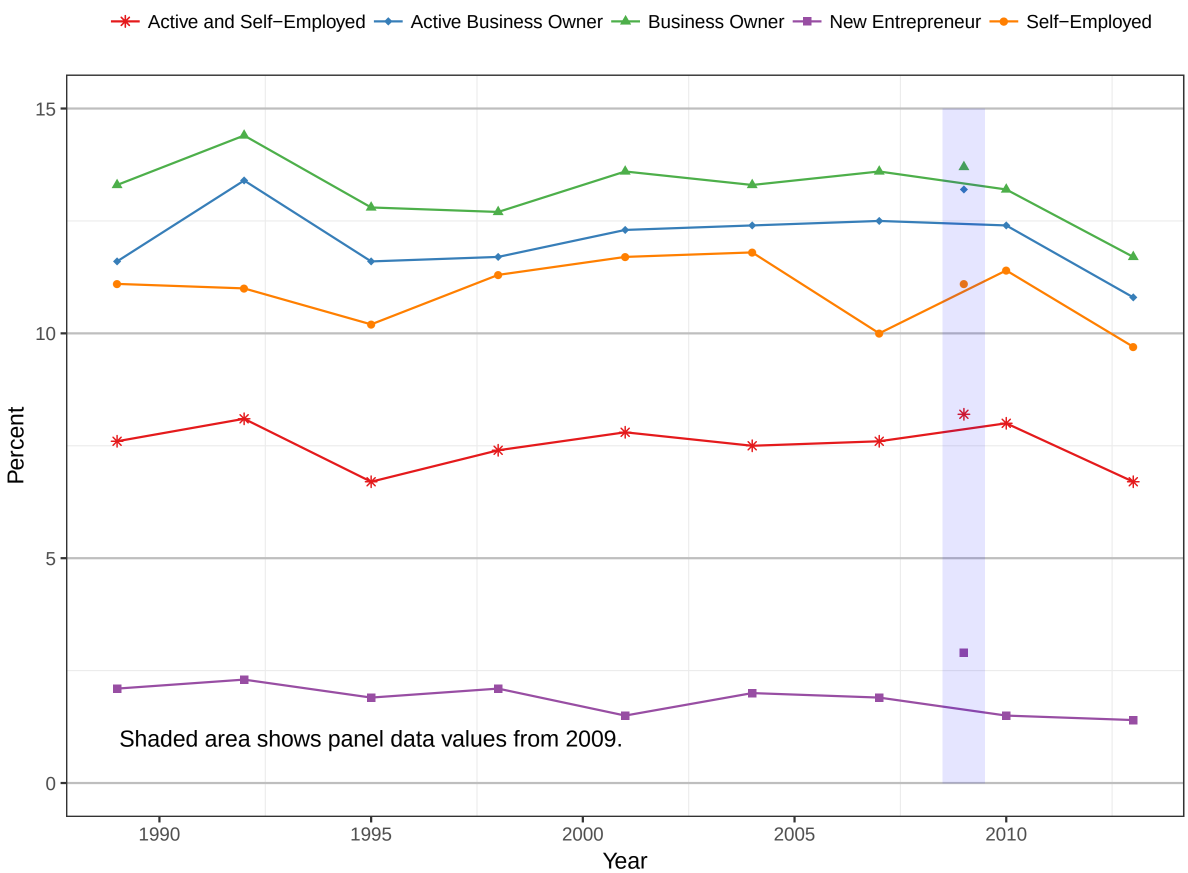

Figure 2.1: Percentage of entrepreneurs in the U.S. population, various definitions.

Note: "New Entrepreneur" is 2-or-less-year-old "Active Business Owner". Source: Survey of Consumer Finances.

The SCF contains detailed information on household incomes, assets and debts. As such, I am able to separate housing related debt into various components. In this paper I am interested in the use of home equity in obtaining business financing, and so I treat all second mortgages and home equity lines of credit (HELOCs) as home equity loans. Thus, this definition is separate from primary mortgages, but contains all other debt backed by a house. Though there are differences in the structure of second mortgages and HELOCs (i.e. second mortgages have a fixed term, interest rate and payment schedule whereas HELOCs have an indefinite term and variable interest rate) both are subordinate to the primary mortgage.

2.3 Summary Statistics

Figure 2.2 shows how the sample evolves over the crisis. Both mean median age increase by two years, reflecting the length of the panel. The effects of the crisis are readily apparent. Total assets fall, for the most part caused by dropping house values which also causes home equity to fall. Despite the drop in home equity home equity loans and HELOC limits increase. Interestingly, income shows little change.

For the remainder of this paper, I call a worker any respondent who is not an entrepreneur. The differences between workers and entrepreneurs becomes apparent in Figure 2.3. First, note the higher nonfinancial income of entrepreneurs and the sharper drop in mean income during the recession.[20] Second, entrepreneurs are much more asset-rich as is well-documented in other papers.[21] Third, total debt does not change much, a reflection of the constancy of aggregate total debt reported earlier. Fourth and finally, note that home equity loan balances are much higher for entrepreneurs and are also disproportionately higher relative to house value. Furthermore, home equity loans and HELOC limit increase for entrepreneurs despite falling house value and constant total debt.

2.4 Importance of Home Equity for Financing Existing Businesses

Access to home equity loans effects the rate of entrepreneurship in two ways: (1) by providing funding to incumbent entrepreneurs when business financing is deficient, and so lowering the probability of exit; and (2) by providing funding for entrants, which will be discussed in

[20]Nonfinancial income is reported in order to avoid changes in income caused by fluctuations in financial markets which were a notable feature of this period. It is total income less interest, dividend and capital gains income.

[21]For instance, Cagetti & De Nardi (2006).

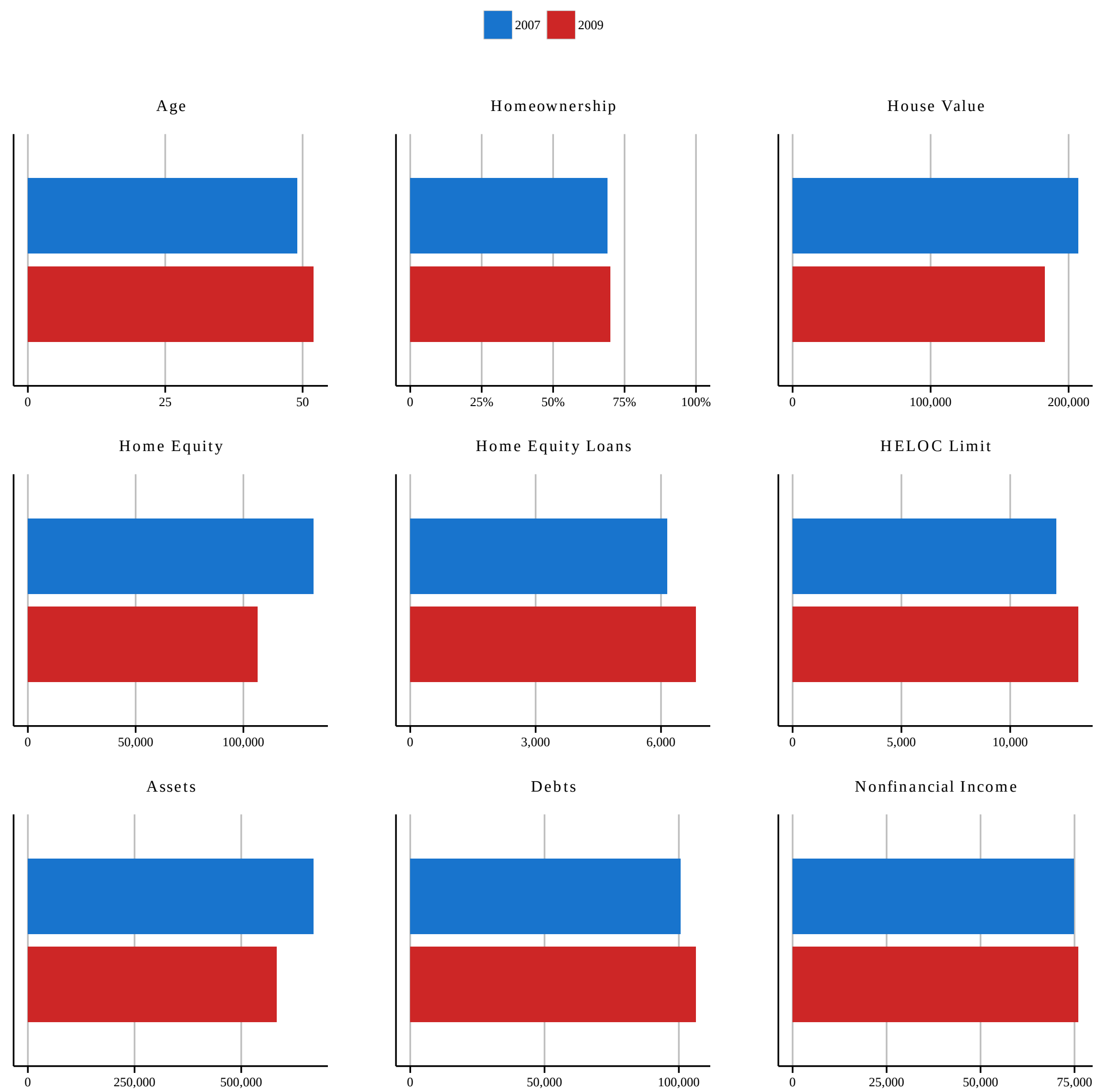

Figure 2.2: Means of key variables.

Note: nonfinancial income is total income less interest, dividend and capital gains income. Supporting data along with standard deviations and medians can be found in the Appendix, Table A.2. Source: Survey of Consumer Finances.

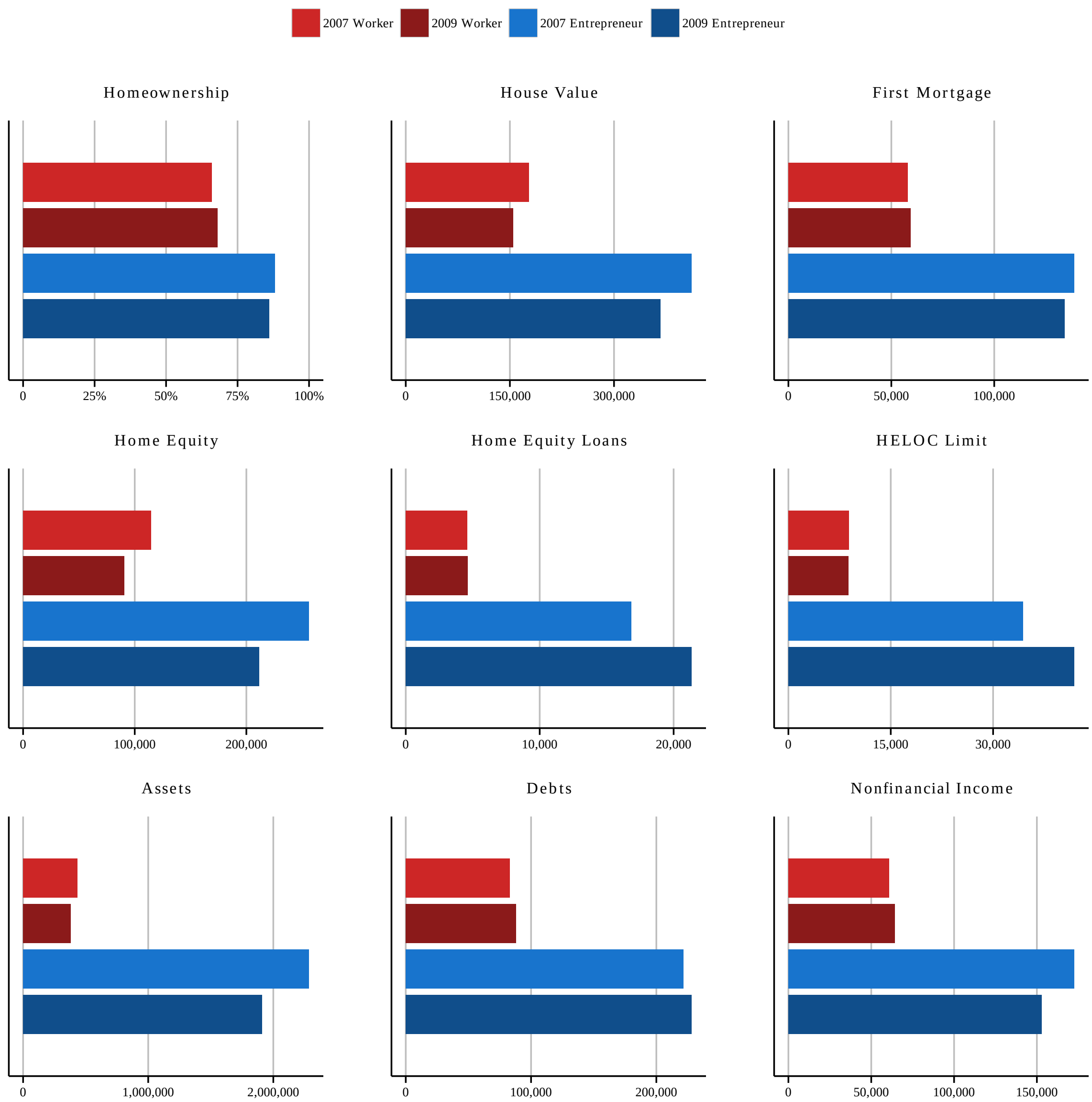

Figure 2.3: Means of key variables, Workers and Entrepreneurs.

Note: nonfinancial income is total income less interest, dividend and capital gains income. Supporting data along with standard deviations and medians can be found in the Appendix, Table A.3. Source: Survey of Consumer Finances.

Section 2.5. For incumbent entrepreneurs, I find that those with more access to personal loans had a higher higher rate of survival: entrepreneurs in 2007 that remained entrepreneurs in 2009 had more home equity and larger HELOC limits than those that had exited entrepreneurship by 2009. In fact, homeowners were 10 percentage points less likely to exit when compared to non-homeowners (18% to 28%). These results are supported by a probit regression which controls for differences in, for instance, business value and income.

The differences between exiting entrepreneurs and survivors can be found in Figure 2.4. In 2007, entrepreneurs that survive and remain entrepreneurs through 2009 had a higher mean house value (51%), on average had more home equity (62%) and a higher HELOC limit (134%). Surviving entrepreneurs also had proportionally higher house-related debt. The home loan-to-value ratio, which is the ratio of all house-related debt (including primary mortgages and home equity loans) to the value of the house, was 21% higher for surviving entrepreneurs than it was for exiting entrepreneurs in 2007 (0.63 to 0.52).

Furthermore, the finances of surviving and exiting entrepreneurs changed in different ways between 2007 and 2009. Though both types of entrepreneurs saw similar drops in house value (surviving: 12%, exiting: 15%) continuing entrepreneurs increased borrowing against their home while exiting entrepreneurs borrowed less. Reflecting this, the average home loan-to-value ratio for surviving entrepreneurs increased by 11%, from 0.63 to 0.70. Part of this increase was caused by a lower house value, but home equity loans also increased substantially, by 21%. In contrast, exiting entrepreneurs saw a decrease in their home loan-to-value ratio, by 8%, from 0.52 to 0.48. Mean first mortgage and home equity loan balances also decreased for this group as they exited entrepreneurship. So, entrepreneurs that survived the credit crisis increased borrowing against their home, while exiters decreased borrowing, though both groups saw a similar drop in their house value.

One might think that differences in the finances of exiters and survivers was caused by differing homeownership rates and not the amount housing wealth, *per se*. In fact, this pattern is repeated when only homeowners are considered. Figure 2.5 shows the relevant results for this sub-sample. In 2007, house value was 40% higher for survivors and home equity was 50% higher. Also in 2007, home equity loan balances were twice as large for continuing entrepreneurs relative to exiters. By 2009, mean house value for surviving entrepreneurs decreased proportionally less than the mean house value for exiting entrepreneurs. This caused the difference in house value to increase but, despite this, mean home equity of survivors decreased relative to exiters, reflecting the increase in house-related borrowing for surviving entrepreneurs. Again, home equity loans increased by 21% for survivors but did not change for exiters and the home loan-to-value ratios are moving in different directions.

Perhaps more exiters are simply retiring and the observed changes and differences in their

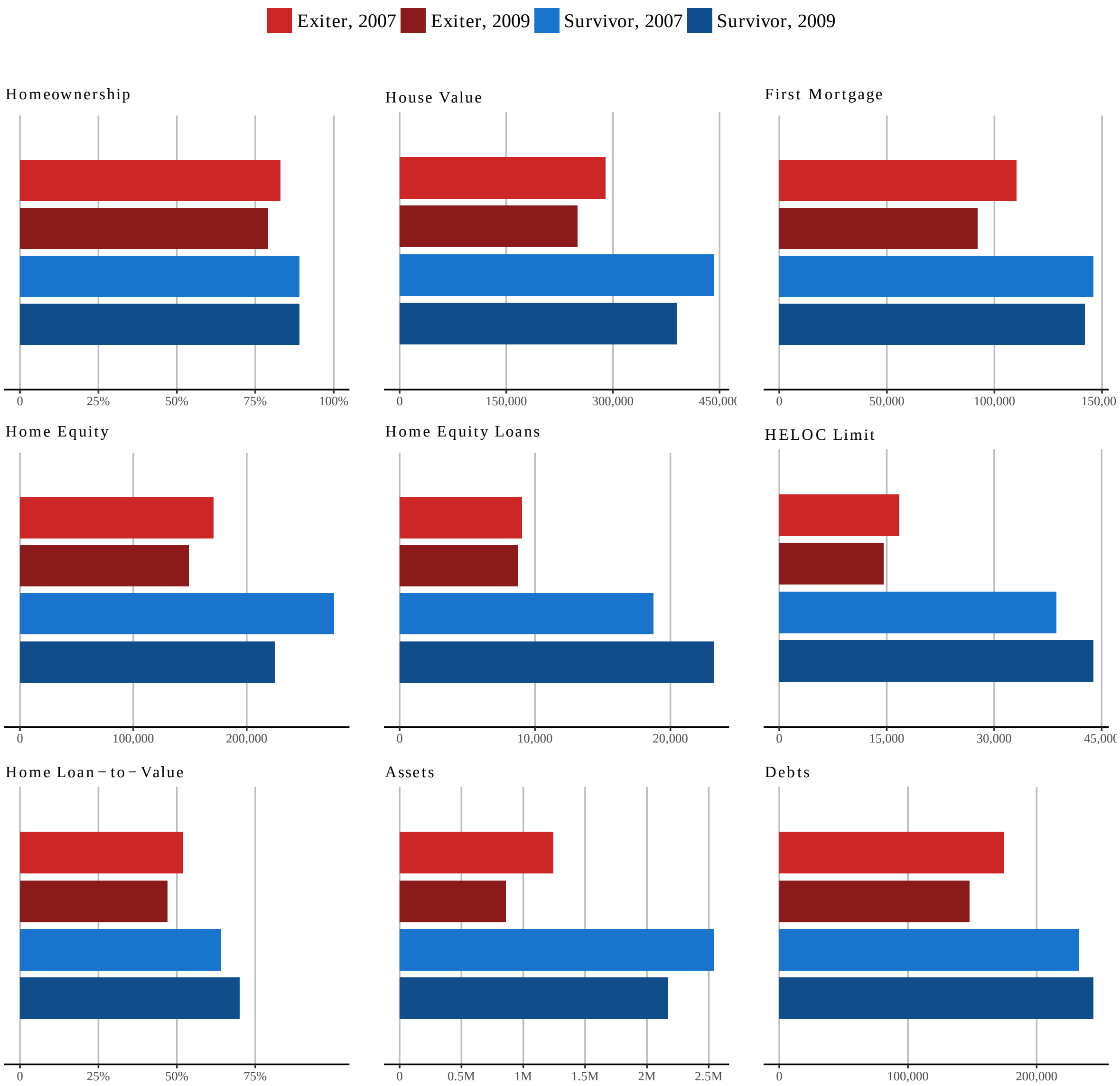

Figure 2.4: Summary statistics, 2007 Entrepreneurs.

Source: Survey of Consumer Finances.

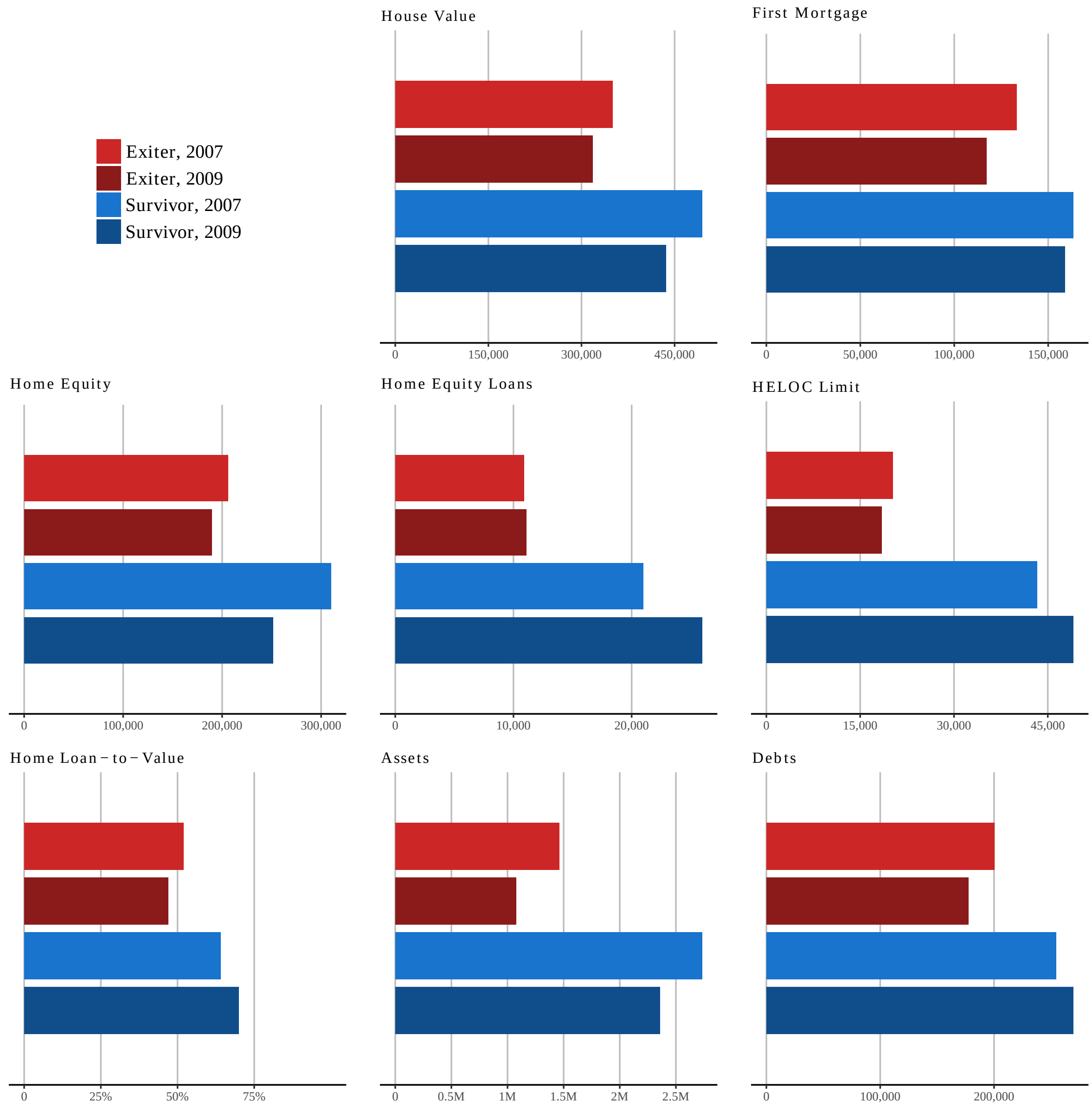

Figure 2.5: Summary statistics, 2007 Entrepreneurs who are also homeowners.

Source: Survey of Consumer Finances.

finances are caused by this fact and not by the increased use of personal loans to finance the business. By considering only those households that are working age I show that this is not the case. Table 2.1 contain the results for working-age entrepreneurs.[22] The pattern of decreasing home loan-to-value ratio for exiters and increasing loan-to-value ratio for survivors is repeated.

Table 2.1: Summary statistics, 2007 working-age entrepreneurs.

	2007		2009	
	Exit	Continue	Exit	Continue
Non-financial Income	110,098	183,288	89,151	158,824
	80,600	83,000	70,000	90,000
Assets	977,279	2,289,085	594,345	1,909,180
	465,400	714,900	284,400	623,800
Debts	181,052	239,213	155,602	250,516
	140,000	149,200	88,400	159,000
House Value	273,976	426,056	221,611	369,341
	200,000	270,000	170,000	250,000
First Mortgage	120,486	151,222	103,421	149,703
	90,000	105,000	82,000	107,000
Home Equity Loans	7,923	18,901	10,114	22,302
	0	0	0	0
HELOC Limit	17,481	38,026	15,174	40,174
	0	0	0	0
Home Equity	145,567	255,933	108,076	197,336
	62,000	118,000	44,000	80,000
Homeownership	0.84	0.89	0.79	0.88
	1.00	1.00	1.00	1.00
Home Loan-to-value	0.57	0.67	0.55	0.77
	0.58	0.49	0.64	0.57
N	109	833	98	781

Note: First row is the mean, second the median.
Source: Survey of Consumer Finances.

Increased borrowing against the value of home for surviving entrepreneurs is indicative of an increased use of personal loans to finance the business, when paired with the opposite change for exiters. As further evidence that housing wealth is being used by entrepreneurs for business financing, I document a more frequent use of home equity loans by survivors and a less frequent use by exiters. Table 2.2 shows a net decrease in the use of home equity loans by exiters (4.4%, the difference between "stop" and "start" in the exit row) and a net increase by survivors (1.2%) whereas non-entrepreneurs show no change. I document the same pattern

[22]Working age is defined here as under 65.

in the use of personal collateral or guarantees to fund the business.[23] In 2007 16% of eventual exiters were using such guarantees while 20% of survivors were doing the same. By 2009 the fraction of continuing entrepreneurs that had used personal guarantees had increased to 24.2%. These results are found in Table 2.3.

Table 2.2: Frequency of home equity loan use, by entrepreneur type.

Entrepreneur Type	HEL Use			
	Never	Stop	Start	Always
Worker	83.5	4.0	4.0	8.6
Exit	78.7	7.0	2.6	11.8
Survive	66.4	8.3	9.5	15.8
Total	81.2	4.5	4.6	9.7

Note: Percent by row.

Source: Survey of Consumer Finances.

Table 2.3: Frequency of personal guarantee or collateral use, by entrepreneur type.

Entrepreneur Type	Personal Asset Use			
	Never	Stop	Start	Always
Exit	84.0	16.1	-	-
Survive	68.0	7.9	12.0	12.1
Total	74.7	7.7	9.7	7.9

Note: Percent by row.

Source: Survey of Consumer Finances.

The results above show that continuing entrepreneurs had more access to personal loans than did exiters and that their use of these loans increased during a period of tight business credit. That exiting entrepreneurs reduced their use of home equity borrowing is telling: it suggests that continuing entrepreneurs were using these funds for their business.[24] However, to determine the effect of having more equity on survival, one must consider other factors such

[23] In the SCF respondents are asked *"Are you (or your family living here) using personal assets as collateral or did you have to cosign or guarantee any loans for (this business/these businesses)?"*

[24] Herkenhoff, Phillips & Cohen-Cole (2016) also study the SCF and draw a similar conclusion from observational evidence. Robb & Robinson (2012) obtain direct evidence from the Kauffman Survey and also conclude that personal borrowing is used as a source of start-up funding for many entrepreneurs.

as higher business value or income.[25]

To control for other possible influences on the survival probability of entrepreneurs, I use the following probit model to estimate the contribution of housing related debts and assets:

$$\Pr(\text{Entrepreneur in 2009}|\mathbf{X}) = \Phi(\mathbf{X}\beta)$$

where

$$\mathbf{X}\beta = Demo\beta_d + Income\beta_i + Assets\beta_a + Debt\beta_b + Home\beta_h$$

and Φ is the cumulative distribution function of a standard normal distribution. The sample for this regression is all entrepreneurs in 2007. The dependent variable is a dummy for entrepreneur status in 2009 and the independent variables are all 2007 values. This method was chosen as the regression results are meant to be interpreted as a forecast of entrepreneurial status in 2009 as determined by the state of household finances in 2007, specifically housing related assets and debts. As such, only 2007 data should be available for the forecast. For different specifications *Home* is either (1) a homeownership dummy and HELOC limit; (2) home equity; (3) home equity loan balances and house value; or (4) all of the preceding. These variables were separated to avoid collinearity issues.[26]

Table 2.4 shows the results of this regression, which support the hypothesis that homeownership and home equity loans improved the survival probability of entrepreneurs that had access to this channel of lending.[27] The coefficients for homeownership, home equity and home equity loan balances are all positive and significantly different from zero. Furthermore, the coefficient for HELOC Limit, which is the total funds which can be drawn against home equity through an established line of credit, is also positive and significant. Interestingly, having more liquid assets or other assets do not seem to be predictive of survival. This suggests that entrepreneurs are specifically able to use their home, as opposed to other assets, to obtain personal loans for the business. Higher business value is also predictive of survival, as more valuable businesses may more readily weather poor credit conditions and low demand.

The marginal effects of the key variables can be found in Table 2.5. When holding all other variables at their means, the marginal effect of homeownership decreases the probability

[25] An alternative story is that "better" entrepreneurs are richer and have more housing wealth, thus the increased survival probability is due to entrepreneur quality, not higher levels of home equity, *per se*. The probit model estimated in this section includes measures that are correlated with business quality to control for this effect. Another influence on the results that I am unable to control for is the vulnerability of the business, i.e. the security of the business' finances.

[26] A description of each variable can be found in Table A.4.

[27] "Correctly Classified" measures the accuracy of the regression by classifying observations dependent on whether the predicted probability is greater or less than half. The percentage of observations that are correctly classified can increase or decrease for different cutoffs.

Table 2.4: Estimated coefficients, probit model to measure effect on entrepreneur status in 2009.

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
Age	0.0677***	0.0756***	0.0747***	0.0665***	Business Value				
	(379.95)	(437.52)	(431.64)	(372.38)	Second Quintile	0.333***	0.340***	0.336***	0.334***
Age Squared	-0.000731***	-0.000808***	-0.000801***	-0.000725***		(282.79)	(289.57)	(286.30)	(283.07)
	(-418.24)	(-475.82)	(-471.15)	(-414.40)	Third Quintile	0.874***	0.868***	0.864***	0.876***
Education (H.School)	-0.234***	-0.193***	-0.208***	-0.229***		(681.66)	(678.94)	(676.18)	(681.89)
	(-121.87)	(-101.71)	(-109.31)	(-118.76)	Fourth Quintile	0.912***	0.912***	0.905***	0.910***
Education (SomeColl)	-0.292***	-0.252***	-0.268***	-0.292***		(685.33)	(687.44)	(680.09)	(682.51)
	(-145.41)	(-126.99)	(-134.39)	(-144.63)	Fifth Quintile	1.359***	1.355***	1.336***	1.352***
Education (College)	-0.173***	-0.146***	-0.164***	-0.179***		(863.40)	(860.19)	(839.66)	(851.42)
	(-94.78)	(-80.38)	(-89.65)	(-97.17)	Service Industry	-0.00429***	0.00000305	-0.00490***	-0.00781***
Race (White)	0.104***	0.125***	0.122***	0.101***		(-4.95)	(0.00)	(-5.66)	(-8.99)
	(95.31)	(116.06)	(113.42)	(93.02)	Personal Collateral	-0.356***	-0.351***	-0.353***	-0.355***
Household Size	-0.00460***	0.00244***	-0.000191	-0.00577***		(-301.95)	(-299.18)	(-300.95)	(-301.65)
	(-12.74)	(6.85)	(-0.54)	(-15.95)	Own Home	0.206***			0.194***
Married	-0.118***	-0.0933***	-0.0925***	-0.125***		(151.95)			(134.38)
	(-101.25)	(-80.62)	(-80.04)	(-106.42)	HELOC Limit	0.103***			0.0956***
Delinquent	0.0153***	-0.0120***	-0.0131***	0.0102***		(176.63)			(158.77)
	(6.77)	(-5.33)	(-5.81)	(4.49)	Home Equity		0.0169***		0.0112***
Bankrupt (ever)	0.192***	0.185***	0.184***	0.199***			(130.45)		(34.44)
	(136.19)	(132.54)	(130.88)	(140.97)	Home Equity Loans			0.0171***	-0.0000131
Years at Address	0.00192***	0.00395***	0.00459***	0.00192***				(17.67)	(-0.22)
	(36.79)	(77.32)	(89.66)	(35.36)	House Value			0.0157***	-0.0000360
Non-Financial Income	3.75e-08***	1.44e-08***	8.27e-09***	1.09e-08***				(140.74)	(-1.29)
	(24.52)	(9.92)	(6.74)	(8.44)	Constant	-1.147***	-1.274***	-1.242***	-1.097***
Liquid Assets	-0.000249***	-0.000318***	-0.000297***	-0.000271***		(-231.02)	(-258.23)	(-250.79)	(-219.38)
	(-33.62)	(-44.76)	(-42.06)	(-38.09)					
Other Assets	0.00000637***	-0.00000683***	-0.00000869***	-0.00000735***					
	(8.46)	(-8.91)	(-11.68)	(-9.98)					
Credit Card Balance	0.0292***	0.0305***	0.0265***	0.0324***	Observations	1,145	1,145	1,145	1,145
	(86.84)	(91.41)	(77.99)	(94.97)	Correctly Classified	80.45%	80.44%	80.44%	80.44%

Sample is restricted to entrepreneurs in 2007. Business Value is relative to first quintile. Education is relative to no high school.

t statistics in parentheses. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$. Unit is $10,000 where appropriate.

Table 2.5: Marginal effects, probit model to measure effect on entrepreneur status in 2009.

	Model			
	(1)	(2)	(3)	(4)
Own Home	0.0530 (0.00)			0.0497 (0.00)
HELOC Limit	0.0250 (0.00)			0.0023 (0.00)
Home Equity		0.0041 (0.00)		0.0003 (0.00)
Home Equity Loans			0.0042 (0.00)	-0.0000 (0.83)
House Value			0.0038 (0.00)	-0.0000 (0.20)

Note: p values in parentheses; All other variables fixed at means.

of exit from 21% to 13%. Increasing an entrepreneurs HELOC limit by $10,000 decreases the probability of exit by 2.5%. An increase of $25,000 in home equity decreases the probability of exit by 1%. The marginal effect of home equity loan balances deserves some discussion. In the sense that additional home equity borrowing in 2007 precludes additional borrowing against home equity one would expect the marginal effect of 2007 home equity loan balances to be negative. However, if home equity loan borrowing was effective in improving an entrepreneurs chance of survival or if the quality of the business is positively correlated with both probability of survival and access to credit (for instance if a bank loan officer is able to discern the quality of the business) one would expect the marginal effect to be positive.

In sum, access to personal financing through homeownership, specifically in the form of home equity loans, increased the probability of survival for entrepreneurs in 2007. Homeowners were less likely to exit, a finding which is robust to controlling for various measures of business quality and other types of assets. As an indication that these loans were used to finance business expenditures, borrowing against the home increased on both the intensive and extensive margin for surviving entrepreneurs, decreased for exiters, and did not change for non-entrepreneurs.

2.5 Importance of Home Equity for Financing Business Entry

After discussing the effect that access to personal loans has on the survival of entrepreneurs in Section 2.4, I turn now to new entrepreneurs. Considering the evidence for incumbent entrepreneurs using home equity loans to ease financing constraints, one would expect 2009 entrants to have more available home equity and a higher homeownership rate than 2007 entrants. Indeed, I find entrants in 2009 had more housing wealth than entrants in 2007 and so had more available collateral to secure financing. Specifically, entrants in 2009 had more valuable houses and more available home equity than entrants in 2007, both before and during the housing crash. 2009 entrants also had larger HELOC limits and were borrowing less against the value of their home at the time of entry.

However, the homeownership rate of new entrepreneurs decreases slightly between 2007 and 2009. That home equity was more important to homeowners in 2009 and the homeownership rate didn't change indicates that any change in the non-homeowner rate of entry into entrepreneurship matched that of homeowners, despite tighter credit conditions. Instead, tightened credit conditions seemingly manifested in less valuable business starts for non-homeowning entrepreneurs in 2009, compared to 2007.

2.5.1 Identifying New Entrepreneurs

I identify new entrepreneurs in 2009 by determining which 2009 entrepreneurs were not entrepreneurs in 2007. Thus, an entrepreneur is new if he or she entered entrepreneurship in either 2008 or 2009: a two-year period. The dataset that I employ is a 2-period panel so I am unable to apply this method to determine which entrepreneurs were new in 2007, as their status before 2007 is unknown. Also, the panel survey offers no direct information on the tenure of a business.

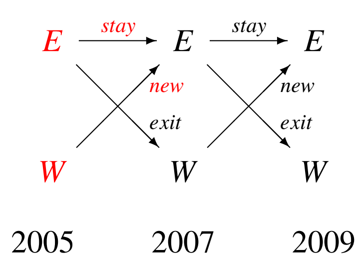

Figure 2.6: Flow of entrepreneurs across periods.

Note: In order to separate the pool of entrepreneurs (E) in 2007 into those that were entrepreneurs in 2005 (*stay*) and those that were "workers" (W) in 2005 (*new*) additional information from the 2007 Survey of Consumer Finances is required.

To remedy this, I supplement the 2007-2009 Survey of Consumer Finances panel with the full 2007 Survey of Consumer Finances cross-section. This allows me to use questions regarding the entrepreneur's business that were asked as part of the usual cross-section survey but not in the 2009 re-interview. Most relevant for this section is the inclusion of a question which asks the year the business was started, which is asked of the top three businesses by value. To maintain consistency with the definition of a new entrepreneur in 2009 (using the panel survey), I call an entrepreneur new in 2007 if the business was opened in 2006 or 2007. Furthermore, if the entrepreneur has more than one business I then use the year the first actively-managed business was started. This constrains the definition to include only those households who entered entrepreneurship in 2006 or 2007, and precludes entrepreneurs that started second or third businesses in this two-year period. This is necessary as these households were already entrepreneurs and so would not have been classified as new in 2009. Again, this aspect of the definition is consistent with that used in 2009 as data on multiple businesses is aggregated in the panel survey.

2.5.2 Results

If tightened credit constraints induced 2009 entrants to use more housing wealth to secure financing, or to do so more frequently, than entrants in 2007, one would expect to see more valuable houses and more home equity amongst entrants in 2009. As can be seen in Table 2.6, this is indeed the case. Both mean and median house prices are over a fifth higher in 2009 than in 2007. The differences in home equity are also readily apparent: mean home equity of 2009 entrants is 63% higher than in 2007, and the median is 14% higher. This housing wealth was also more readily accessible for 2009 entrants: 29% of entrants in 2009 had established HELOCs (one form of home equity loans) whereas only 11% of 2007 entrants had access to this form of borrowing. In 2007, of those that had established HELOCs, the mean and median limits were $124,145 and $83,000 for entrants. Despite house prices decreasing, the mean and median limit for entrants in 2009 increased to $144,765 and $100,000, respectively. Primary mortgage balances were also lower for 2009 entrants. All told, the ratio of borrowing against the home to the value of the home is lower for 2009 entrants than it is for 2007 entrants.[28] So, not only did 2009 entrants have more home equity to borrow against, they also had more access to immediately available credit.

Table 2.7 repeats the above analysis for homeowners only. As one would expect, the pattern above is repeated though the differences are much larger. New entrepreneurs in 2009 had higher valued homes (25% higher mean, 6% median) than 2007 entrants despite the housing crash. Home equity differences are substantial: 2009 entrants had 67% higher mean (53% higher median) home equity than did 2007 entrants. Reflecting this, mean HELOC limits (inclusive of those without HELOCs) are over two and a half times greater for 2009 entrants. As well, the home loan-to-value ratio was higher for 2007 entrants (0.62) than it was in 2009 (0.55), leaving 2009 entrants with more home equity to borrow against. So, housing wealth was seemingly more important for entry during the credit crisis, especially for homeowners.

[28]The home loan-to-value ratio is measured as the sum of primary mortgage balances, second mortgage balances, outstanding home equity loans, and HELOC balances divided by house value.

Table 2.6: Comparison of new entrepreneurs in 2007 and 2009.

	2007		2009	
	New	All	New	All
Homeownership (2007)	0.77	0.88	0.74	0.86
	1.00	1.00	1.00	1.00
Homeownership (2009)	-	-	0.76	0.86
	-	-	1.00	1.00
House Value (2007)	234,420	411,962	327,620	416,270
	160,000	250,000	220,000	250,000
House Value (2009)	-	-	287,614	366,934
	-	-	200,000	240,000
Home Equity (2007)	101,516	256,198	209,586	261,992
	44,000	110,000	76,000	110,000
Home Equity (2009)	-	-	165,800	211,474
	-	-	50,000	82,000
Home Equity Loans (2007)	13,371	16,834	12,219	17,281
	0	0	0	0
Home Equity Loans (2009)	-	-	14,918	21,351
	-	-	0	0
HELOC Limit	14,038	34,391	35,247	41,913
	0	0	0	0
Primary Mortgage	119,533	138,930	106,897	134,109
	110,000	92,000	68,000	88,000
Home Loan-to-value	0.48	0.54	0.42	0.58
	0.50	0.38	0.40	0.42
Liquid Assets	38,013	64,900	28,650	74,253
	4,200	11,300	5,500	10,000
Other Assets	307,984	900,337	475,576	812,898
	53,800	171,000	90,000	152,000
Business Value	214,561	908,665	198,396	654,493
	20,000	81,000	10,000	50,000
Non-Financial Income	83,636	172,599	118,357	152,890
	61,000	83,000	82,000	90,000
Debt	173,825	221,556	173,140	228,221
	147,900	140,000	122,000	133,000
N	69	1,145	133	1,132

Note: first row is the mean, second the median.

Source: Survey of Consumer Finances.

Table 2.7: Comparison of new entrepreneurs in 2007 and 2009, homeowners.

	2007		2009	
	New	All	New	All
Homeownership (2007)	1.00	1.00	0.88	0.96
	1.00	1.00	1.00	1.00
Homeownership (2009)	-	-	1.00	1.00
	-	-	1.00	1.00
House Value (2007)	302,890	467,917	413,337	469,525
	230,000	300,000	260,000	300,000
House Value (2009)	-	-	378,784	424,941
	-	-	245,000	275,000
Home Equity (2007)	131,167	290,996	269,607	298,738
	70,000	139,000	115,000	139,000
Home Equity (2009)	-	-	218,356	244,905
	-	-	108,000	115,000
Home Equity Loans (2007)	17,276	19,121	16,025	19,926
	0	0	0	0
Home Equity Loans (2009)	-	-	19,647	24,726
	-	-	0	0
HELOC Limit	18,139	39,063	46,420	48,539
	0	0	0	0
Primary Mortgage	154,447	157,801	140,781	155,310
	149,000	109,000	120,000	112,000
Home Loan-to-value	0.62	0.62	0.55	0.67
	0.71	0.45	0.57	0.52
Liquid Assets	47,194	71,260	36,026	83,589
	4,200	12,000	9,400	12,000
Other Assets	371,255	993,561	597,337	918,434
	88,000	204,500	185,000	194,000
Business Value	197,044	967,829	256,251	718,684
	17,000	89,000	17,000	50,000
Non-Financial Income	92,795	185,053	133,036	164,603
	73,000	89,000	100,000	95,400
Debt	215,568	244,784	223,127	260,451
	184,000	161,000	180,000	172,000
N	58	1,075	110	1,058

Note: first row is the mean, second the median.

Source: Survey of Consumer Finances.

As a demonstration of the uniqueness of housing wealth vis-à-vis entrepreneurial financing, Table 2.8 shows the differences in new non-homeowners in 2007 and 2009. Here sample size becomes an issue, but some conclusions can be drawn. First, both liquid assets and other assets (total assets less liquid assets and business value) of entrants in 2007 and 2009 were very similar.[29] That I find no difference between the asset levels of these two groups, as well as the lower amount of assets available to them when compared to other entrepreneurs, suggests that no more collateral was required of non-homeowner entrepreneurs during the credit crisis and that little is required during "normal" conditions. That is not to say that the credit crisis had no effect. There was a large difference in the value of a new entrepreneur's business in 2007 and 2009: the mean value in 2007 is over 17 times higher than in 2009, and the median value is over 20 times higher. So, tightened credit standards did not result in any changes in the asset levels of (non-homeowning) entrants, but instead resulted in much smaller business starts.

Table 2.8: Comparison of new entrepreneurs in 2007 and 2009, non-homeowners.

	2007		2009	
	New	All	New	All
Liquid Assets	6,583	18,078	5,384	15,196
	3,600	3,600	1,600	3,000
Other Assets	91,366	213,984	91,455	145,321
	38,000	38,000	9,100	18,000
Business Value	274,534	473,074	15,878	248,445
	106,000	50,000	5,000	20,000
Personal Collateral	28,221	18,072	0	60,135
	0	0	0	0
Non-Financial Income	52,280	80,912	72,047	78,801
	45,000	50,000	54,000	60,000
Debt	30,911	50,544	15,443	24,344
	24,300	20,200	2,700	11,000
N	11	70	23	74

Note: first row is the mean, second the median.
Source: Survey of Consumer Finances.

Though the effects of tightened credit conditions appear in the housing wealth available to entrants with a home, the rate of homeownership amongst entrants did not increase between 2007 and 2009, and in fact dropped from 77% to 76%.[30] This is surprising as new entrepre-

[29] These results are statistically significant using unranked and ranked median tests and a *t*-test of the means.

[30] The decrease in homeownership is probably understated in the SCF panel as survey respondents acquire homes between 2007 and 2009 and so the 2009 homeownership rate is upwardly biased. The unconditional upward bias in the 2009 homeownership rate is roughly 2%.

neurs in 2009 had more housing wealth than those in 2007, suggesting that tightened credit conditions necessitated the increased use of personal wealth to finance the business, and so one might expect *more* homeownership in 2009. Table 2.9 shows a proportional increase in the homeowner and non-homeowner rate of entry, leaving the homeownership rate roughly constant. Though it may be surprising that the rate of entrepreneurship increased (especially for non-homeowners who started much smaller businesses in 2009 when compared to 2007), Fairley (2013) finds that higher local unemployment rates increase the probability that a household starts a business.

Table 2.9: Fraction of entrepreneurs in the U.S. population, by homeownership.

	2007 (CS)			2007 (PNL)			2009 (PNL)		
	HO	RT	All	HO	RT	All	HO	RT	All
New Entrepreneurs	1.56	0.31	1.88	1.25	0.36	1.61	2.21	0.70	2.91
Incumbent	9.39	1.23	10.62	9.95	1.16	11.11	9.15	1.09	10.25
All Entrepreneurs	10.95	1.54	12.49	11.20	1.52	12.72	11.36	1.80	13.16

Notes: (1) Fraction of total population is reported; (2) New entrepreneurs are those that started within 2 years of survey year, Incumbents are entrepreneurs who aren't new; (3) HO - homeowner, RT - non-homeowner; (4) CS - cross-section survey, PNL - panel survey. Source: Survey of Consumer Finances.

The above results show that using personal loans to fund a business is important for new entrepreneurs and that differences may exist in the financing options available to homeowners and non-homeowners. These differences may be caused by the tendency of non-homeowners to start smaller business, and not solely homeownership. Table 2.10 offers a comparison of small and large new entrepreneur starts in 2007 and 2009.[31]

In regards to small businesses (one or fewer employees), more housing wealth was available to 2009 entrants. New entrepreneurs in 2009 had 28% more home equity on average (54% median) and 5% higher house values on average (23% median). HELOC limits were over 6 times greater for small 2009 entrants, when compared to small 2007 entrants (including households without HELOCs). Mirroring the broader picture, the home loan-to-value ratio was lower for 2009 small entrants (0.35 mean, 0.22 median) than it was 2007 small entrants (0.45 mean, 0.59 median). Small entrants in 2009 had more housing wealth than those in 2007, and so had more available collateral that could be used to obtain financing.

Entrepreneurs who start large businesses also seemed to be more housing rich in 2009, though the picture is less clear. Mean house values and home equity are 48% and 221% higher, respectively (median house values are 149% higher in 2009.) However, counter to the previ-

[31] The SCF asks "*(In total how/How) many people work for (these businesses/this business), including you (or anyone in your family living here)?*" I use this measure as a proxy for business size.

Table 2.10: Comparison of new entrepreneurs in 2007 and 2009, by size.

	Small		Large	
	2007	2009	2007	2009
Homeownership	0.74	0.73	0.82	0.79
	1.00	1.00	1.00	1.00
House Value	238,034	250,274	230,210	339,987
	155,000	190,000	160,000	238,000
Home Equity	113,205	145,327	87,901	194,514
	54,000	83,000	40,000	25,000
Home Equity Loans	9,528	16,843	17,847	12,218
	0	0	0	0
HELOC Limit	7,760	49,173	21,351	15,715
	0	0	0	0
Primary Mortgage	115,301	88,104	124,462	133,256
	104,000	39,000	117,000	112,000
Home Loan-to-value	0.45	0.35	0.52	0.51
	0.59	0.22	0.49	0.57
Liquid Assets	44,677	14,873	30,252	47,974
	4,200	4,000	4,600	7,600
Other Assets	202,306	327,597	431,075	683,127
	43,200	80,000	122,050	150,500
Business Value	122,105	91,768	322,251	347,949
	15,000	0	50,000	40,000
Number of Employees	0.76	0.50	16.34	45.95
	1.00	0.00	3.00	3.00
Non-Financial Income	79,892	101,062	87,998	142,613
	50,000	75,000	61,000	91,000
Debt	166,599	150,379	182,241	205,063
	115,700	71,000	171,000	184,060
N	32	64	37	69

Notes: (1) small is one or fewer employees; (2) first row is the mean, second the median. Source: Survey of Consumer Finances.

ously discussed results, median home equity is 38% for lower 2009 large entrants and HELOC limits are also lower (27% mean, 26% median). Here liquid and other assets may have played a larger role: new large entrants had more liquid assets and non-housing, non-business assets in 2009 than in 2007.

In sum, entrants in 2007 had less housing wealth to borrow against than those in 2009 suggesting the credit crisis induced nascent entrepreneurs to use their housing wealth to finance their new business. This result is especially apparent for homeowners and relatively small businesses. For non-homeowners, available wealth for 2007 entrants was very similar to that of 2009 entrants. In this case, the credit crisis may have manifested itself through much smaller business values in 2009.

Though the effect of the credit crunch regarding the housing wealth of new entrepreneurs is, for the most part, clear, in light of the potential effects of business size for example, it would be informative to determine the effect of higher housing wealth controlling for such effects. To this end I estimate a probit model.

I estimate the following model using the sub-sample of entrepreneurs in 2007 and again separately in 2009:

$$\Pr(\text{New Entrepreneur}|\mathbf{X}) = \Phi(\mathbf{X}\beta)$$

where X is a vector of independent variables and Φ is the cumulative distribution function of a standard normal distribution. In this model, X includes, among other variables: demographics variables such as age, education and race, a dummy variable for homeownership, home equity, liquid assets in quintiles, other assets (apart from house value, business value and liquid assets), total income, credit card balance, housing payments, and the debt service ratio, which is a measure of monthly debt payments to monthly income.

Also included are ratio variables that capture differences in the composition of income and debt payments of a household. For instance, a new entrepreneur's wage income may be a larger portion of their total income as they are more likely to have worked in the previous year.[32] These ratio variables include, as a fraction of non-financial income,[33] wage income, retirement income and other income, and as a fraction of total debt payments, housing payments (including mortgage, rent and property tax) and consumer debt payments (credit card and line of credit payments).

The regression results are reported in Table 2.11 and a description of the variables is in Table A.4. In 2009, though not in 2007, being in a higher quintile by home equity positively predicts new entrepreneurship, relative to all entrepreneurs. This suggests that new entrepreneurs needed more available housing wealth to pledge and borrow against in order to finance a

[32]The SCF separates business and self-employment income from wage income.

[33]Non-financial income is defined as total income less interest, capital gains, and dividend income.

Table 2.11: Estimated coefficients, probit regression to determine new entrepreneurs.

	2007	2009		2007	2009
Age	0.0832***	-0.000946**	Income	-0.000686***	0.00217***
	(191.28)	(-2.81)		(-34.32)	(112.30)
Age Squared	-0.000706***	-0.0000594***	Income Squared	6.54e-08***	-7.47e-07***
	(-153.20)	(-17.58)		(47.42)	(-85.65)
Education			Liquid Assets		
High School	0.0230***	-0.0300***	2nd Quintile	-0.228***	0.253***
	(6.88)	(-12.59)		(-127.36)	(147.84)
Some College	0.110***	-0.125***	3rd Quintile	-0.859***	0.184***
	(31.62)	(-49.22)		(-378.21)	(103.23)
College	0.401***	-0.158***	4th Quintile	-1.243***	0.389***
	(126.35)	(-67.76)		(-498.57)	(204.19)
Race (White)	-0.250***	0.105***	5th Quintile	-0.576***	0.0230***
	(-168.01)	(77.54)		(-228.00)	(9.92)
Household Size	0.114***	0.126***	Other Assets	0.0000511***	0.0000146***
	(200.79)	(304.64)		(11.63)	(10.23)
Married	0.195***	-0.461***	Have Retirement	-0.00144***	0.00639***
	(90.91)	(-335.36)	Assets∗Age	(-39.13)	(231.19)
Risk Aversion			Wage Income	1.122***	0.351***
Little Risk	-0.0785***	0.114***		(563.30)	(239.98)
	(-29.23)	(41.22)	Retirement Income	-0.115***	1.378***
Average Risk	0.449***	-0.117***		(-28.26)	(462.15)
	(177.42)	(-43.38)	Other Income	3.388***	2.303***
Substantial Risk	0.423***	0.152***		(555.91)	(462.37)
	(149.95)	(53.90)	Credit Card Balance	-0.0337***	0.0779***
Years at Address	-0.0570***	-0.00532***		(-53.83)	(215.69)
	(-539.46)	(-74.17)	Debt Payments	-0.0956***	-0.0261***
Years at Job	-0.0644***	-0.0245***		(-28.83)	(-13.85)
	(-729.31)	(-426.08)	Housing Payments	-0.372***	1.616***
Own Home	-0.0444***	-0.361***		(-56.26)	(274.93)
	(-16.62)	(-98.14)	Consumer Debt Pay.	-0.255***	1.299***
Home Loan to Value	-0.0127***	-0.119***		(-36.12)	(204.47)
	(-17.18)	(-71.80)	Debt Service Ratio	0.554***	-0.374***
Home Equity				(370.92)	(-223.07)
2nd Quintile	0.362***	0.601***	Log Business Value	-0.162***	-0.0832***
	(159.72)	(219.92)		(-374.67)	(-259.66)
3rd Quintile	-0.408***	0.0588***	Employees	0.0000809***	0.000135***
	(-153.58)	(19.80)		(31.64)	(91.29)
4th Quintile	-0.867***	0.368***	Personal Collateral	-0.00295***	0.0000426***
	(-294.65)	(116.07)		(-55.52)	(29.28)
5th Quintile	-1.063***	0.339***	Service Industry	0.368***	0.636***
	(-309.91)	(96.49)		(273.38)	(535.07)
Net Worth (percentile)	0.0302***	-0.00998***	Constant	-3.487***	-1.299***
	(522.30)	(-275.02)		(-288.68)	(-113.02)
Observations	1,145	1,132	Correctly Classified	90.81%	84.75%
Observations (weighted)	12,641,588	11,997,571	Pseudo R^2	0.3648	0.2291

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Variables in units of $10,000 where appropriate. See Table A.4 for description of variables.

new business in 2009. New entrepreneurs are also more likely to have used personal collateral to obtain funding for their business in 2009, though less likely in 2007. However, in both 2007 and 2009 new entrepreneurs are less likely to own a home, relative to all entrepreneurs. Entrepreneurs that have more liquid assets are less likely to be new entrepreneurs in 2007 and more likely to be new in 2009, a reflection of increased credit standards which in 2009 required a new entrepreneur to provide more personal collateral in all forms. The marginal effects of the key variables can be found in Table 2.12.

Table 2.12: Marginal effects, probit regression to determine new entrepreneurs.

	2007		2009	
Variable	dy/dx	p	dy/dx	p
Own Home	-.00684	(0.00)	-.08821	(0.00)
Home Equity				
2nd Quintile	.06705	(0.00)	.12821	(0.00)
3rd Quintile	-.05996	(0.00)	.01036	(0.00)
4th Quintile	-.10745	(0.00)	.07266	(0.00)
5th Quintile	-.12195	(0.00)	.06629	(0.00)
Liquid Assets				
2nd Quintile	-.03876	(0.00)	.05175	(0.00)
3rd Quintile	-.12083	(0.00)	.03661	(0.00)
4th Quintile	-.15352	(0.00)	.08323	(0.00)
5th Quintile	-.08865	(0.00)	.00431	(0.00)
Personal Collateral	-.00040	(0.00)	.00001	(0.00)
Log Business Value	-.02186	(0.00)	-.01768	(0.00)

Note: All other variables fixed at means.

There are significant demographic differences in the pool of new entrepreneurs in 2007 and those in 2009. For instance, new entrepreneurs tend to be older relative to all entrepreneurs in 2007, but younger in 2009. This is also true of education level: new entrepreneurs are more likely to be college graduates in 2007, but less likely in 2009. Consistent between 2007 and 2009, new entrepreneurs are more likely to have higher wage income relative to total income. New entrepreneurs also tend to own less valuable businesses. Significant changes between 2007 and 2009 include, relative to all entrepreneurs, in 2009 entrants now have more retirement income (relative to total income), have higher credit card balances, have more housing and consumer debt (relative to total debt), but have lower debt service ratios.

These results support the previous findings: that housing wealth was an important source of personal collateral for entrepreneurs in 2009. Specifically, new entrepreneurs in 2009 had more available home equity to borrow against than new entrepreneurs in 2007. In fact, home equity became so important that new entrepreneurs in 2009 had more home equity than incumbent entrepreneurs whereas during the 'looser' credit conditions of 2007 they had less. For entrants without homes, tightened credit standards and a lack of housing wealth resulted in less valuable businesses. These results are robust to controlling for the effects of business value and business size.

2.6 Conclusion

I make the striking observation that, despite house prices decreasing during the Great Recession, home equity loan balances increased, all while total debt did not change. The primary source of the increased use of home equity borrowing was entrepreneurs. I interpret this as evidence of binding financing constraints for entrepreneurs.

As entrepreneurs were not able to borrow during the credit crunch due to more stringent loan standards and less bank lending to small businesses, home equity loans allowed entrepreneurs to survive the crisis. Personal loans were a substitute for business loans. This confirms studies such as Quadrini (2000) that find that wealth is important for the entrepreneurship decision but deepens the understanding of how, exactly, wealth is used by entrepreneurs. In this case, housing wealth is used to ease credit constraints and to aid survival and entry. Of entrepreneurs in 2007, surviving entrepreneurs had higher rates of homeownership and higher house values relative to those that did not survive. Furthermore, continuing entrepreneurs increased borrowing against their home, while exiting entrepreneurs did not. Entrants in 2009 had more available housing wealth than those in 2007.

As discussed above, the drop in home equity resulted in 2007 entrepreneurs hiring fewer employees and an increased exit rate, which in turn resulted in job loss as well. Using the population weights provided with the SCF, changes in home equity, and the results obtained above we can derive a rough estimate of the change to employment. On average, the drop in home equity caused a drop of 0.23 employees per business for surviving entrepreneurs, roughly 5% of the observed drop per business (4.3). Furthermore, the drop in home equity caused roughly 28,000 entrepreneurs to exit, bringing with them 340,000 employees.

King & Levine (1993) show that effective financial systems that support entrepreneurship can have a significant impact on economic growth. This paper studies one channel that entrepreneurs might employ to finance their business when the usual financial channels are not available to them. Though entrepreneurs were able to use home equity loans to survive the Great Recession, it was not costless as more household wealth was exposed to business risk at the height of the recession. Considering the influence entrepreneurs have on growth and employment (see, for example, Adelino, Schoar, & Severino, 2012) policies that ease borrowing constraints for entrepreneurs, such as the 7a loan program from the Small Business Administration, are a potentially beneficial means to improve aggregate conditions.

Chapter 3

The Role of Public Information and Credit Ratings in the Corporate Bond Market

3.1 Introduction

Firms with AAA credit ratings are disappearing. While in 1985 there were 34 firms with a AAA rating, by 2011 there were only 4.[1] The decline in top rated debt has also taken place at the AA level; between 1985 and 2010 the number of firms issuing AAA or AA debt dropped by 70%, while the number of firms issuing A or BBB debt increased by 77% and those issuing speculative grade debt increased by 129%. Overall the number of firms with a bond rating increased by 59% (see Figures 3.1 and 3.2.)

Why is the ratings distribution shifting towards more mediocre ratings? The answer to this question is important as bonds are now a larger share of corporate liabilities. In the Federal Reserve Board Flow of Funds Data, the share of total liabilities held in bonds grew by 26.5% between 1985 and 2010. Corporations are increasingly choosing bond and equity financing over other securities and bank financing.[2] Furthermore, the size the corporate bond market is massive; nonfinancial corporations had $4,691 billion of outstanding bond debt in 2010.[3] Considering the size and growth of this market, the underlying cause of the ratings shift may have a substantial effect on capital markets.

Credit ratings are ostensibly used by investors to determine how likely a firm is to default on its outstanding debt. Firms with AAA credit ratings are less likely to default than those rated AA, A, and so forth. On top of this, credit ratings are also a signal of the firm's general

[1] The four firms, as rated by Standard & Poor's, are Johnson & Johnson, Automatic Data Processing Inc., Microsoft Corp. and Exxon Mobil Corp.

[2] The change in share of total corporate liabilities was 20.7%, -76.7%, and -67.1% for equity, securities and bank financing, respectively.

[3] $7,167 billion outstanding at the end of 2016, per the most recent data available.

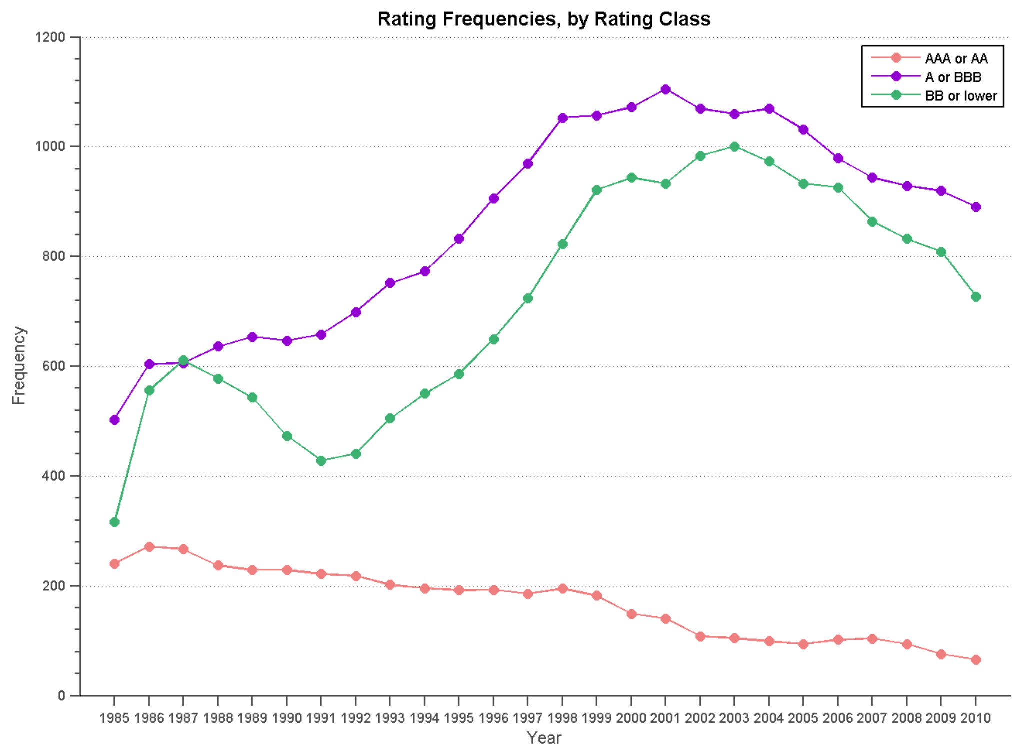

Figure 3.1: Frequency of ratings by group: AAA or AA, A or BBB, and all speculative grade.

competence, as it is very difficult to achieve the highest ratings. As these ratings are useful to investors, firms will consult with ratings agencies prior to selling their debt.[4]

In part, the need for credit ratings is regulatory: many large, institutional investors are required to hold only investment grade bonds (BBB or higher). Additionally, it is difficult for firms to credibly relay this information directly to investors, and the auditing process would be very onerous for an individual investor. Thus the credit rating agencies are able to exploit some efficiencies of scale. There is a trade-off for firms however: they must devote resources to non-productive ratings activities in order to satisfy the requirements of the credit rating agencies, on top of the fee for the rating service itself.[5] For instance, a firm is required to hold cash on hand to satisfy the requirements for a particular rating. If credit ratings were not required to sell corporate bonds, firms might be able to reallocate their resources to increase profits.

Considering the value of a credit rating, a natural question arises: why are the highly rated firms disappearing? I argue that firms are no longer willing to pay the cost to achieve high ratings. To this point:

[4]Though it is possible to issue debt without consulting with a credit ratings agency, almost all firms do. Nevertheless, both Standard & Poor's and Moody's will issue a rating regardless of the firm's participation.

[5]This is typically a percentage of the size of the bond issue.

Figure 3.2: Share of ratings by group: AAA or AA, A or BBB, and all speculative grade.

> "Scores of big companies have lost their AAA status in recent years as it became seen in board rooms as more of a straitjacket than a path to riches."
>
> (Eric Dash, New York Times, August 2, 2011)

To capture this change, I propose the following mechanism. As credit ratings have value as a signal of firm "quality" in the sense that they provide investors with information about the future performance of the firm, they are an alternative to other publicly available channels of firm information. These channels include SEC 10K filings, which contain pertinent financial data from public firms and are now provided electronically, as well as media such as the Wall Street Journal Online and Bloomberg. With the proliferation of this information, investors now have direct access to firm information which may convince them to purchase lower-rated bonds. Firms no longer need to rely solely on a credit rating as a signal of their type, as the demand for their bonds is now also dependent on this costless, public channel.

The topic was originally discussed in the financial press, from whom multiple answers have emerged. Besides firms' unwillingness to pay for improved ratings, other suggestions include investors simply having a larger appetite for risk so they are more willing to purchase lower rated bonds, and investors no longer placing much stock in corporate bond ratings. Though seemingly disparate, I argue that these three answers are essentially the same. Firms will lower their rating and reduce the associated costs if they are able to sell their debt at a lower rating. This would be possible if the demand for lower investment grade bonds has increased relative to high investment grade bonds. In effect, there is lower demand for top ratings from both investors *and* firms.

To formalize this story, I construct a model that contains a "peacock" problem: the firm must divert resources to non-productive rating activities in order to improve its expected credit rating. Firms are endowed with a project and differ only in the probability that this project will pay off with the higher return. Both the credit rating and a costless public signal are correlated with the firm's type. This type is unknown to everyone, including the firm. As the firm learns something about its type from the public signal, this will influence the decision to invest in the rating process. Once this decision is made, a credit rating is formed for all firms. Knowing the public signal and the credit rating, investors then decide whether to invest in the firm's project. To capture the proliferation of information over the period in question, I increase the correlation of the public signal with a firm's type (the "accuracy" of the signal). Under general conditions, the resulting change in the distribution of credit ratings matches the change observed in the data.

The mechanism works as follows. Investors are unable to observe an individual firm's type but have access to credit ratings and the public signal. Firms with projects that have a higher expected payoff will be more likely to receive a high public signal and more likely to earn a high rating. The investors are then able to offer lower interest rates to those firms with higher ratings and signals. Additionally, a higher rating will increase the probability that a firm receives an investment. As the accuracy of the signal increases, firms and investors learn more about the type of the firm, which may induce firms to forego investing to achieve a high rating. In equilibrium, an increase in the accuracy of the public signal will result in fewer firms with high ratings and more firms with mediocre and low ratings.

The primary testable implication of the model is the increase in the dispersion of interest rates within a rating class. When the accuracy of the public signal is low, the interest rates given to two firms with the same rating and different signals will be closer than when the accuracy is high. In effect, the difference between interest rates increases with the accuracy of the signal as investors are more sure that these firms have different underlying types. Using data from the *Mergent Fixed Income Securities Database*, I show that this pattern is borne out between 1990 and 2010.

There are alternative explanations that need to be explored. One must consider that firms may be, in fact, more likely to default. That is, there exist fewer firms in 2010 with the same expected default rate as the AAA-rated firms in 1985. It is very difficult to measure a change in default probabilities as the default rate for AAA and AA-rated firms is very close to zero. A proxy for default probability is the leverage ratio, which is a measure of the indebtedness of firm relative to some form of its value, either assets or equity. It follows that a firm with a higher debt burden to value ratio will be more likely to default than one with either lower debt or higher firm value, as the latter will find it easier to service its debt. I calculate and plot the average leverage ratios for different cohorts of AAA and AA-rated firms over the relevant period in Figure 3.3. The leverage ratios are roughly stable for each cohort. This indicates that higher-levered firms do not seem to be driving the change in the ratings distribution.

It may be the case that the distribution of bond ratings has changed for reasons not related to firm behaviour. For instance, credit rating agencies may have changed the standards used to determine a firm's rating (or may be applying them differently), while the relevant measures of firm behaviour have remained constant. If this was the case, the within-rating average leverage ratios would either increase or decrease depending on whether that rating class has become relatively more or less prone to default. By computing the average leverage ratio within a rating by year, I show that this is not the case. Average leverage ratios have changed very little over the relevant period. The results can be seen in Figure 3.4.

Another possibility is that top rated firms are merging. To examine this I do two things. First, I show that the assets controlled by all AAA firms as a fraction of GDP is decreasing.[6] Second, as there are very few firms with AAA ratings, I can follow the cohort of AAA firms in 1985 to determine the evolution of their debt, including whether the debt rating changed, the debt was retired, or the firm merged with another. As can be seen in Table 3.1, though some firms do merge when viewed over the entire horizon, for the most part the firms end up at a lower rating.

In all markets, the rating system is designed to measure relative credit risk. The credit rating agencies (CRAs) assert that a rating does not measure absolute default probability and that a rating does not constitute investment advice. The purpose of this position is to ensure protection from liability claims and to continue their status as a Nationally Recognized Statistical Rating Organization (NRSRO). This designation is important as only ratings from such an organization may be used to satisfy legal obligations as to which debt may be held by large, institutional investors. An example of such an investor is a pension fund which is required to hold only investment grade debt.[7] Another example is any bank that has committed itself to the Basel Accords, which specify a capital requirement based on the rating composition of the bank's assets.

[6]If AAA firms were merging, it may be the case that the sum of assets controlled by AAA-rated firms stayed roughly constant.

[7]Debt is considered investment grade if it has a rating of BBB or above. Debt rated BB or lower is deemed speculative grade or high yield.

Apart from the large U.S. banks, CRAs such as Standard & Poor's, Moody's, and Fitch have suffered the most criticism in the wake of the recent financial crisis and the Great Recession. This criticism is perhaps justified in regards to how the CRAs rated structured finance products, such as mortgage-backed securities and the credit default swaps based on these securities, but it is important to consider the different markets for ratings separately.[8] This is because the structure of the markets differs greatly, and thus the behaviour of CRAs will be different in each.

Though most academic work has focused on the CRA behaviour in the structured finance markets, Manso (2011) considers CRA behaviour in the market for corporate bonds. Where this paper studies an environment with a "passive" CRA, Manso (2011) shows the importance of feedback effects of rating changes when the CRA is able to choose the standards for a rating. The feedback effect begins with a rating adjustment, which in turn affects the interest rate the firm is charged by the markets, as the perceived default risk has changed. As the interest rate changes, the default probability will also change as the debt burden will increase or decrease with the change in interest rate. Thus a CRA which is more "lax" may be preferred to one with more stringent rating criteria. Another branch of the literature that concerns this work is credit rationing in the market for firm debt, which was introduced by Stiglitz & Weiss (1981). The authors show that, under certain conditions, bank credit may be rationed between firms in markets with incomplete information. Bester (1985) extends the model to show that collateral may be used to screen firms and that in this environment at most one submarket will see credit rationing.

Skreta & Veldkamp (2009) show that, as the complexity of the asset increases, the opportunity to "shop for ratings" also increases, as it is more difficult to judge the default probability of the asset.[9] This will then cause inflation in ratings. In a related paper, Bolton, Freixas & Shapiro (2009) show that competition can also cause ratings inflation when investors cannot observe when a rating is produced but not published. Another feature of markets that may pervert CRA incentives is the concentration of issuers. He, Qian & Strahan (2011) found that CRAs favoured large issuers during the recent financial crisis by giving their products higher ratings. This is because the primary source of CRA revenues is payments from issuers (referred to as an "issuer pays" model). In this paper I focus only on the market for corporate bonds, which is not impacted by the above effects, as the market is not dominated by a small number of issuers and corporate bonds are not complex assets.

[8] For articles concerned with these securities see, for instance, Bolton, Freixas & Shapiro (2009) and He, Qian & Strahan (2011) which are discussed later in this paper.

[9] More specifically, when firms solicit multiple rating agencies the resulting difference in ratings will be larger across agencies if the rating produced is noisier. The rating will be noisier if the asset is more complex. Firms then choose the highest rating, and the resulting ratings distribution is "inflated."

The paper proceeds as follows. Section 3.2 provides further detail about the change in the ratings distribution. The model is introduced and relevant results are shown in Sections 3.3 and 3.4. Section 3.5 shows the change in bond price dispersion. Section 3.6 discusses the empirical and analytical results. Section 3.7 concludes.

3.2 The Distribution of Ratings

The firm data used in this project are from COMPUSTAT, including the ratings subset. This data covers all firms that file quarterly reports with the SEC. The ratings subset includes any firm which receives a rating from S&P. I further restrict the sample to include only non-financial firms and firms not primarily owned by the federal government, as the process involved in raising capital may vastly differ with that for non-financial firms. The sample includes 51,610 firm-year observations and 5,319 unique firms.

The most natural reason for the number of AAA ratings to drop is that there are fewer firms with a default probability that is deserving of a AAA rating. That is, there exist fewer firms in 2010 with the same expected default rate as the AAA-rated firms in 1985, assuming the required default rate for a AAA rating is the same. It is very difficult to measure a change in default probabilities as the default rate for AAA and AA-rated firms is very close to zero. So, there may be no difference in the *ex post* default rate despite a different expected default rate *ex ante*.

A useful proxy for default probability is the leverage ratio, which is a measure of the indebtedness of a firm relative to some form of its value, either assets or equity. It follows that a firm with a higher debt to value ratio will be more likely to default than one with either lower debt or higher firm value as the latter will find it easier to retire its debt. I calculate and plot the average leverage ratios for different cohorts of AAA and AA-rated firms over the relevant period in Figure 3.3. The leverage ratios are calculated as the ratio of total liabilities to total assets from individual components reported in COMPUSTAT, at an annual frequency.[10] The leverage ratios are roughly stable for each cohort. This indicates that more highly levered firms do not seem to be driving the change in the ratings distribution.

It may be the case that the distribution of bond ratings has changed for reasons not related to firm behaviour. Primarily, CRAs may have changed the standards used to determine a firm's rating, while the relevant measures of firm behaviour have remained constant. If this was the case the within rating average leverage ratios would either increase or decrease depending on whether that rating class has become relatively more or less prone to default. By computing the

[10]Illiev & Welch (2010) note that two correct alternatives exist, the liabilities to assets ratio and the debt to capital ratio. I compute both and find the same pattern in each.

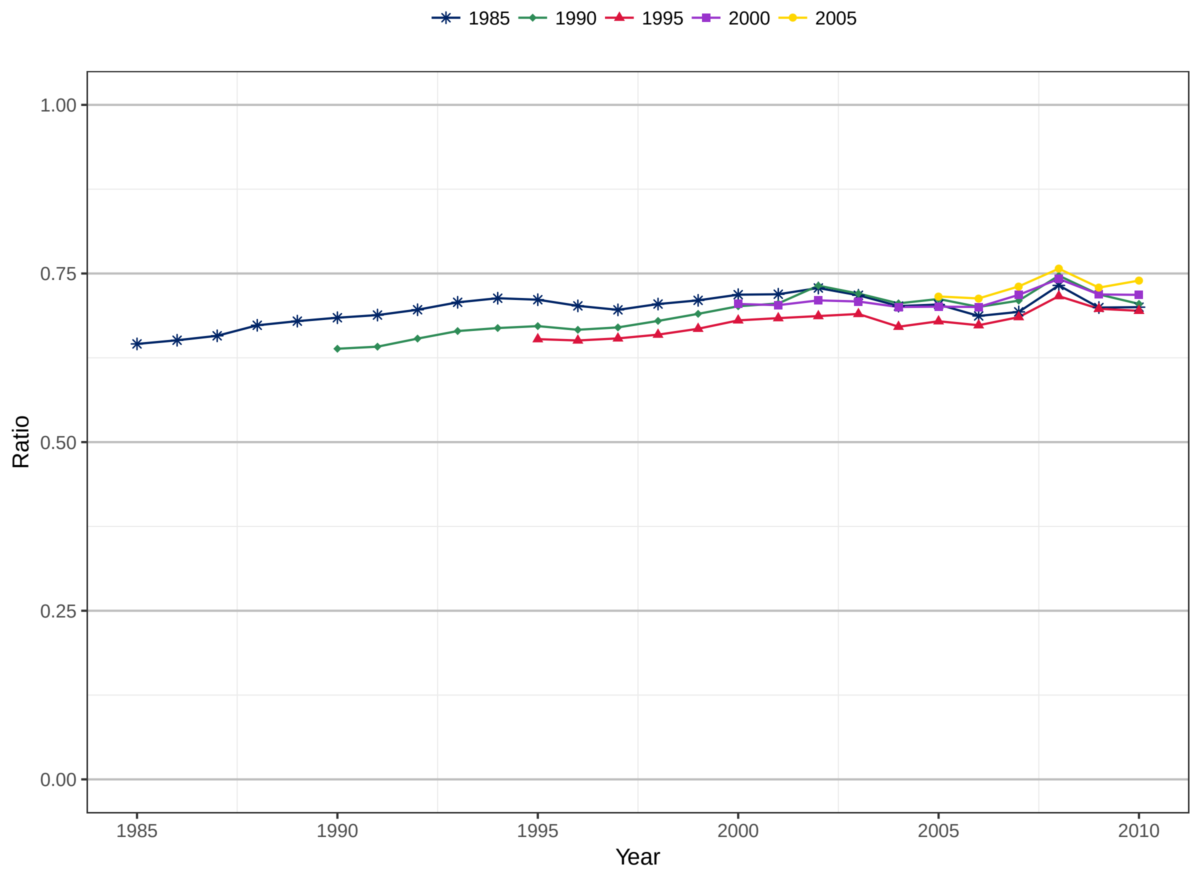

Figure 3.3: Within-cohort average leverage ratios, non-financial corporations. A cohort is as all firms in the sample that were rated AAA or AA in the given year.

average leverage ratio within a rating by year, I show that this is not the case. Average leverage ratios have changed very little over the relevant period. The results can be seen in Figure 3.4.

Another possibility is that highly rated firms are merging. This would imply a decrease in the number of highly rated firms, without a significant drop in the total assets controlled by these firms. By aggregating the assets over ratings and normalizing the levels by dividing by GDP, I show that the share of assets controlled by AAA and AA-rated firms has dropped significantly. The decrease in assets held by AAA and AA-rated firms is commensurate with the decrease in the number of AAA and AA-rated firms. Also, there is an increase in the assets controlled by firms rated A, BBB, or lower, again matching the change in the rating distribution. These series can be seen in Figure 3.5.

To further validate this claim, in Table 3.1 I follow the 1985 cohort of AAA-rated firms. Though 6 of the 34 firms with a AAA rating did eventually exit the sample through merger, a majority of the firms arrived at the end of the sample with a lower credit rating. In fact, all but one of the firms that merged over this period were involved in the conglomeration of regional

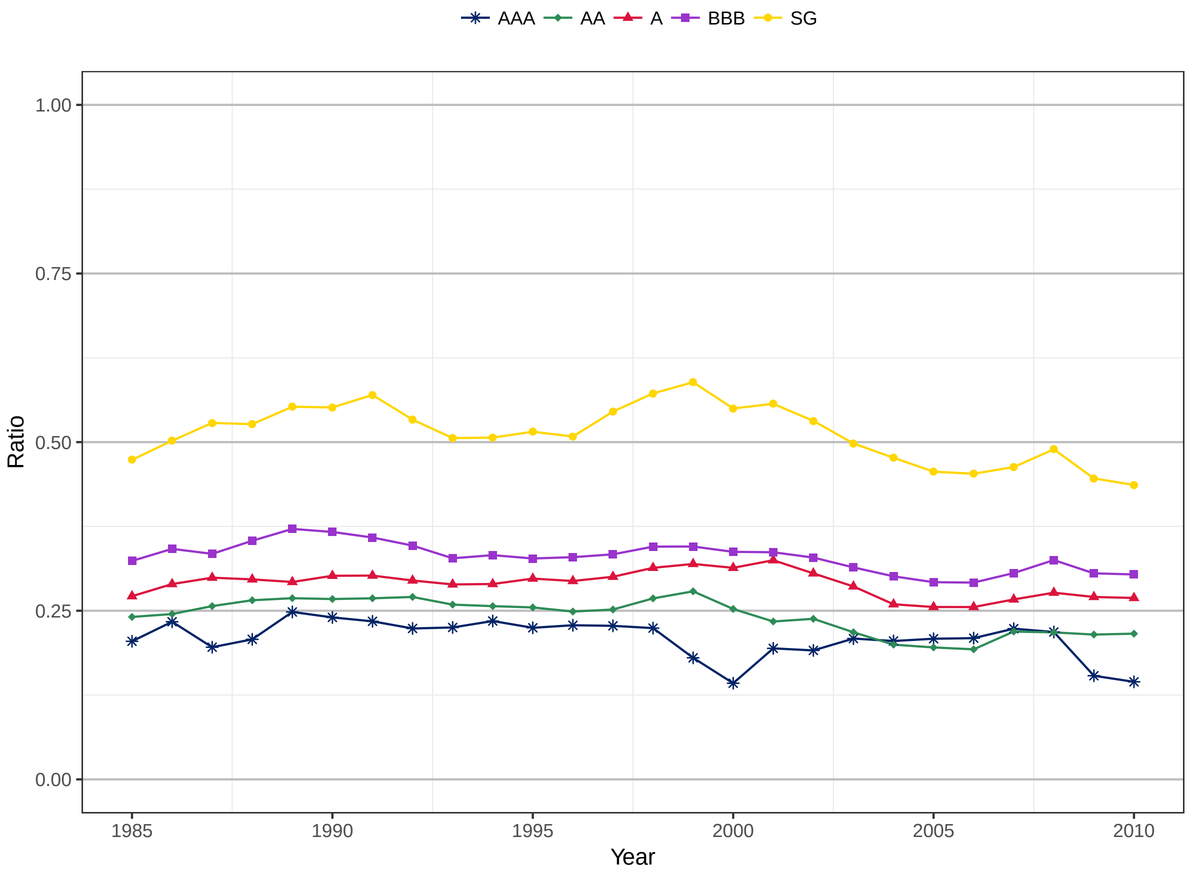

Figure 3.4: Within rating average leverage ratios, non-financial corporations.

telecommunications companies into the national entities in operation today.

A final concern that I have addressed is that, although the distribution of ratings may be changing due to some previously unexplored effect, ratings are now insignificant as bonds make a smaller portion of firm financing. This does not seem to be the case, however. Using the Federal Reserve Board of Governors Flow of Funds dataset, I calculate that the share of corporate bonds to total liabilities has increased by 26% from 1985 to 2010 for all non-farm, non-financial corporations. Of the other broad classes of financing, equity grew by 20.7%, while other securities and bank financing decreased by 76.7% and 67.1%, respectively.

3.3 Model

The aim of the model is to capture the change in the way investors obtain information relevant to their purchase of corporate bonds. Obtaining relevant information directly from the firm is costly for an individual investor, if it is possible at all, whereas rating agencies distribute a

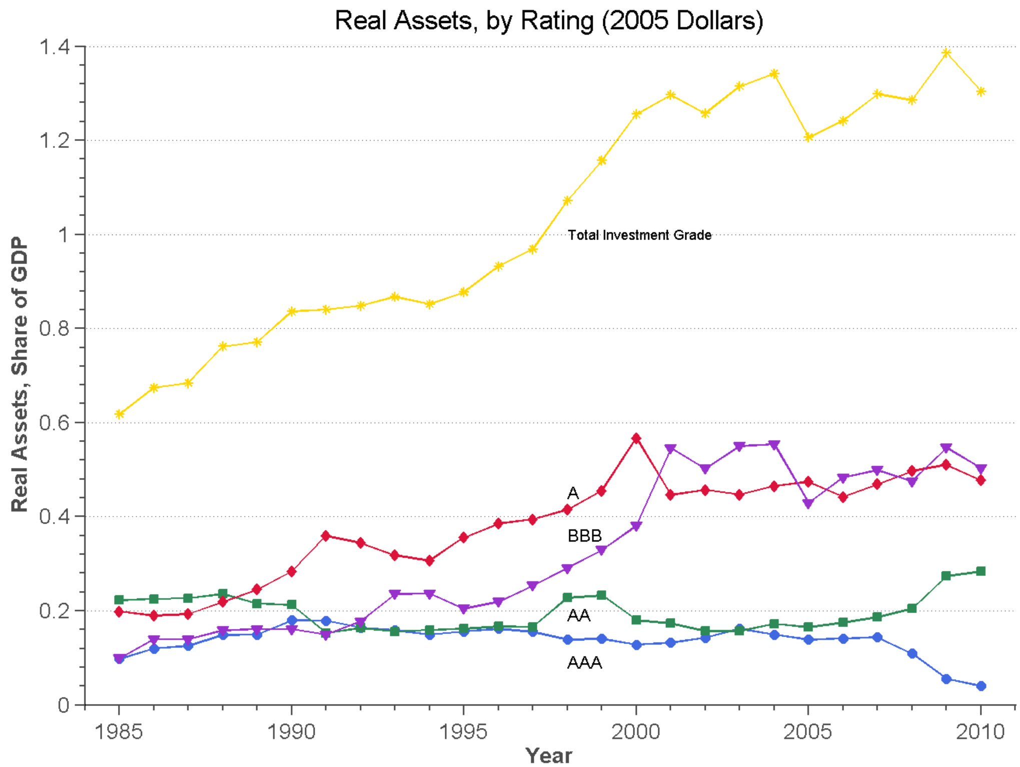

Figure 3.5: Assets controlled by each rating class, non-financial corporations, as a fraction of GDP.

summary of this information in the form of a credit rating. In order to attain a higher rating, firms must devote resources to non-productive ratings activities, such as increasing their cash at hand. As the access to financial information has increased for investors, through channels such as electronic distribution of SEC 10K filings and other sources discussed above, there is now a direct channel between firms and investors. I model this channel as a noisy public signal that is correlated with the probability that a firm's project will result in the higher return, which I call the firm's type.

This section continues with an outline of the environment which describes the players, timing, and information flows. More detail is then provided about the role of public signals and credit ratings. The firm and investor problems follow. The equilibrium concept is then defined, along with the solution to the firm's problem and the investor's decision rule.

3.3.1 Environment

Firms are endowed with a project which will have either a low or high return. The probability of the high return is referred to as the firm's type, $\theta \epsilon \{g, b\}$, is unknown to all. First, a public signal,

Table 3.1: Evolution of circa 1985 AAA firms

	1985	1990	1995	2000	2005	2010
AAA	34	26	17	8	4	1
AA	0	4	8	3	6	8
A	0	1	3	9	6	7
BBB	0	0	1	2	3	3
B	0	1	1	0	0	0
Merged	0	1	2	6	6	6
Retired	0	1	2	6	9	9

$v\epsilon\{h, l\}$, which is correlated with the firm's type is observed by all. The firm then chooses the amount of resources it devotes to non-productive rating activities, $i\epsilon[0, 1]$, knowing the public signal but not their type. Let $c(i)$ be the cost investing i. This investment will increase the probability that the firm receives a high credit rating and lower the probability is receives a low credit rating.

A credit rating, $\kappa\epsilon\{A, B, C\}$, which is also correlated with the firm's type, is then produced by a passive and exogenous credit rating agency and observed by all. The distribution of credit ratings depends on the distribution of θ and i as a firm's rating is influenced by both its type and investment in the ratings process. After observing v and κ, investors decide whether to purchase the firm's debt at the market interest rate, $R(\kappa, v)$. The outcome of the project is then realized and debts are paid.

To make the investment decision non-trivial I assume that probability of the higher return is such that the expected return to low-type projects is lower than the borrowing cost required to satisfy investors. As such, firms would rather walk away from a successful project than pay back investors. Anticipating this, investors will choose not to invest in firms that are known to be "low" type.

3.3.2 Credit Ratings and Public Signals

The credit rating agency assigns a rating, $\kappa\epsilon\,\{A, B, C\}$, to each firm. The probability that a firm receives a given rating is determined by its type, θ, and the amount of resources that the firm chooses to invest in the ratings process, i. Let $\pi_\kappa(\theta, i)$ be the probability that a firm of type θ that invested i receives rating κ. I assume that $\pi_A(\theta, i)$ is increasing in i for every θ whereas both $\pi_B(\theta, i)$ and $\pi_C(\theta, i)$ are decreasing in i. Thus, as firms increase i they increase the probability that they receive a high rating. I assume the rating production functions are linear and obey the following conditions:

$$\pi_A(g,i) > \pi_A(b,i) \quad \forall i \tag{3.1}$$

$$\pi_C(g,i) < \pi_C(b,i) \quad \forall i \tag{3.2}$$

Simply put, these assumptions rule out the possibility of equilibria in which the pool of A-rated firms is more likely to default on average than the pool of C-rated firms. In essence this ensures that the ratings are informative, in that higher ratings are correlated with lower default rates.

The functional forms chosen are as follows:

$$\begin{aligned}
\pi_A(g,i) &= \sigma_1^g + (\sigma_2^g + \sigma_3^g)i \\
\pi_A(b,i) &= (\sigma_2^b + \sigma_3^b)i \\
\pi_B(g,i) &= \sigma_2^g(1-i) \\
\pi_B(b,i) &= \sigma_2^b(1-i) \\
\pi_C(g,i) &= \sigma_3^g(1-i) \\
\pi_C(b,i) &= \sigma_1^b + \sigma_3^b(1-i),
\end{aligned}$$

where

$$\begin{aligned}
\sigma_1^g + \sigma_2^g + \sigma_3^g &= 1 \\
\sigma_1^b + \sigma_2^b + \sigma_3^b &= 1.
\end{aligned}$$

Using these functional forms, $\sigma_1^g > 0$ and $\sigma_1^b > 0$ ensure that Assumptions (3.1) and (3.2) hold.

The noisy public signal, $\nu \epsilon \{H, L\}$, that may be correlated with a firm's type, is seen by investors and firms. The distribution of ν is as follows: $Pr\{H|g\} = Pr\{L|b\} = \omega$ and $Pr\{L|g\} = Pr\{H|b\} = 1 - \omega$. One can interpret ω as the probability that the public signal is accurate, i.e. the probability that good firms get high public signals, and bad firms get low public signals. As constructed, if $\omega > 1/2$ the public signal is informative in that signal H is correlated with type g and L with b.[11]

3.3.3 Firms

Firms differ in their unobservable type, $\theta \epsilon \{g, b\}$. The distribution of θ is as follows: $Pr\{g\} = \lambda$ and $Pr\{b\} = 1 - \lambda$. Firms are endowed with a risky project that will return y with probability

[11] If $\omega < 1/2$, the public signal is still correlated with the firm's type. In this case, the high public signal would be positively correlated with bad firms, and vice versa. Thus the public signal would still be informative, though the labels would not accurately describe the firms.

γ_θ, where $\gamma_g > \gamma_b$, and 0 otherwise. The firm must receive an investment of fixed size $d = 1$ to start the project. The distribution of types is common knowledge.

The timing for firms is as follows. The firm first observes its noisy signal, ν, and then chooses the level of resources to invest in rating activities, i, in order to maximize the expected value of the project net of borrowing costs. At this point the firms do not know their rating and thus the expectation is taken over both the probability the project will return y given ν and the distribution of ratings given ν and i as the rating will influence the borrowing cost $R(\kappa, \nu)$.

Given gross interest rates $R(\kappa, \nu)$, the firm's problem is the following:

$$V(\nu) = \max_i - c(i) + \mathrm{E}_{\theta,h}[\mathbb{1}(\kappa, \nu)(y - R(\kappa, \nu)|\nu)] \tag{3.3}$$
$$\text{subject to: } i\epsilon[0, 1]$$

I assume $c(i)$ is increasing, $c'(0) = 0$ and $c'(1) = \infty$. The indicator function $\mathbb{1}(\kappa, \nu)$ is equal to 1 when an investment is received, and 0 otherwise. It is allowed to depend on κ and ν as both are available to investors when they make their decision to invest.

The benefits of a higher i are lower expected borrowing cost, $R(\kappa, \nu)$, as the expected rating is higher, and an increased probability of receiving an investment. The firm weighs these benefits against the cost of investing in the rating process, $c(i)$. As firms do not observe their type, the public signal determines the level of investment that balances these expected benefits and costs. Thus, as firms that receive the low public signal L may still be of g-type there is still a benefit to investing in the rating. Conversely, firms that receive the high public signal H have some assurance of their being of g-type, but may in fact be of b-type.

3.3.4 Investors

Investors are endowed with one unit of investment capital which they can invest in either firm debt at the market interest rate, $R(\kappa, \nu)$, or government debt at the risk-free interest rate, r. Before making this decision, investors observe a credit rating, κ, and public signal, ν, from the firm. If the investor chooses to purchase firm debt, she will then be repaid $R(\kappa, \nu)$ at the end of the period if the firm honours its debt. Investors face no barriers to entry in the market for debt and investment capital is available in perfectly elastic supply. The expected investor return to firm debt rated κ with signal ν is:

$$\mathrm{E}_\theta[R(\kappa, \nu)|\kappa, \nu]. \tag{3.4}$$

3.3.5 Equilibrium

An equilibrium is a set of interest rates, $\mathbf{R}^* = \{R^*(\kappa, \nu)\}_{\kappa\epsilon\{A,B,C\}}^{\nu\epsilon\{H,L\}}$, and rating investment allocations, $\{i_\nu^*\}^{\nu\epsilon\{H,L\}}$ such that:

1. given $\mathbf{R}^*$, i_ν^* solves (3.3);

2. (free entry condition) investors do not earn excess returns:

$$\mathrm{E}_\theta[R^*(\kappa, \nu)|\kappa, \nu] = r \;\forall \kappa, \nu$$

3.3.6 Solution to the Firm's Problem

Taking first order conditions and solving for i:

$$i_H^* = (c')^{-1} \sum_{\kappa\epsilon\{A,B,C\}} \frac{\omega\lambda\gamma_g\pi'_\kappa(g) + (1-\omega)(1-\lambda)\gamma_b\pi'_\kappa(b)}{\omega\lambda + (1-\omega)(1-\lambda)}(y - R^*(\kappa, H))\mathbb{1}(\kappa, H) \tag{3.5}$$

$$i_L^* = (c')^{-1} \sum_{\kappa\epsilon\{A,B,C\}} \frac{(1-\omega)\lambda\gamma_g\pi'_\kappa(g) + \omega(1-\lambda)\gamma_b\pi'_\kappa(b)}{(1-\omega)\lambda + \omega(1-\lambda)}(y - R^*(\kappa, L))\mathbb{1}(\kappa, L) \tag{3.6}$$

where $(c')^{-1}$ is the inverse marginal cost function. In words, firms choose i such that the marginal benefit of investing in the ratings process (lower interest rates and a higher chance of investment) are equal to the marginal cost.

3.3.7 Investor's Decision

Investors observe a firm's credit rating κ and the public signal ν. Knowing these, and given equilibrium interest rates $\mathbf{R}^*$, the investor will decide to invest if

$$R^*(\kappa, \nu) < y.$$

This ensures the firm will repay if the project is successful. More precisely:

$$\mathbb{1}(\kappa, \nu) = \begin{cases} 1 & \text{if } R^*(\kappa, \nu) < y \\ 0 & \text{if } R^*(\kappa, \nu) \geq y. \end{cases}$$

3.3.8 Interest Rates

Considering the free entry condition for firms, the following are the equilibrium interest rates.

$$R^*(\kappa, \nu) = \frac{r}{\mathrm{E}_\theta(\gamma_\theta|\kappa, \nu)} \tag{3.7}$$

$$R^*(\kappa, H) = r\frac{\omega\lambda\pi_\kappa(g, i_H^*)\gamma_g + (1-\omega)(1-\lambda)\pi_\kappa(b, i_H^*)\gamma_b}{\omega\lambda\pi_\kappa(g, i_H^*) + (1-\omega)(1-\lambda)\pi_\kappa(b, i_H^*)} \tag{3.8}$$

$$R^*(\kappa, L) = r\frac{(1-\omega)\lambda\pi_\kappa(g, i_L^*)\gamma_g + \omega(1-\lambda)\pi_\kappa(b, i_L^*)\gamma_b}{(1-\omega)\lambda\pi_\kappa(g, i_L^*) + \omega(1-\lambda)\pi_\kappa(b, i_L^*)} \tag{3.9}$$

3.4 Results

In this section I first show that firms will decrease i when the accuracy of the public signal increases. This is due to the within-rating class compositional change that occurs when firms change i. This result leads to Proposition 3.4.2, the main result of the paper. Proposition 3.4.2 states that an increase in the accuracy of the public signal will decrease the number of firms with an A rating, while increasing the number of firms with a B or C rating, a shift which matches the real-life change in the ratings distribution described above.

Proposition 3.4.1 *The equilibrium investment in the ratings process for firms with signal ν, i_ν^*, is decreasing in public signal accuracy, ω.*

Proof Suppose not. Then for some ω, i_ν^* increases in ω. This implies that the probability of getting an A (C) rating is increasing (decreasing) for firms with signal ν. The relevant rating production functions are as follows:

$$\begin{aligned}
\Pr(A|g,\nu) &\equiv \pi_A(g, i_\nu) = \sigma_1^g + (\sigma_2^g + \sigma_3^g)i_\nu \\
\Pr(A|b,\nu) &\equiv \pi_A(b, i_\nu) = (\sigma_2^b + \sigma_3^b)i_\nu \\
\Pr(C|g,\nu) &\equiv \pi_C(g, i_\nu) = \sigma_3^g(1 - i_\nu) \\
\Pr(C|b,\nu) &\equiv \pi_C(b, i_\nu) = \sigma_1^b + \sigma_3^b(1 - i_\nu).
\end{aligned}$$

Most directly relevant to investors is the probability that a firm is a certain type, conditional on the observed rating and signal, as the firm's type determines the probability the investment will pay off. Employing Bayes' rule and the law of total probability, the probability that a firm is type θ conditional on observing κ and ν is:

$$\Pr(\theta|\kappa, \nu) = \frac{\Pr(\kappa|\theta, \nu)\Pr(\nu|\theta)\Pr(\theta)}{\Pr(\kappa|\theta, \nu)\Pr(\nu|\theta)\Pr(\theta) + \Pr(\kappa|\bar{\theta}, \nu)\Pr(\nu|\bar{\theta})\Pr(\bar{\theta})}.$$

In particular, the relevant probabilities are:

$$\begin{aligned}
\Pr(g|A,H) &= \frac{\pi_A(g,i_H)\omega\lambda}{\pi_A(g,i_H)\omega\lambda + \pi_A(b,i_H)(1-\omega)(1-\lambda)},\\
\Pr(g|A,L) &= \frac{\pi_A(g,i_L)(1-\omega)\lambda}{\pi_A(g,i_L)(1-\omega)\lambda + \pi_A(b,i_L)\omega(1-\lambda)},\\
\Pr(g|C,H) &= \frac{\pi_C(g,i_H)\omega\lambda}{\pi_C(g,i_H)\omega\lambda + \pi_C(b,i_H)(1-\omega)(1-\lambda)},\\
\Pr(g|C,L) &= \frac{\pi_C(g,i_L)(1-\omega)\lambda}{\pi_C(g,i_L)(1-\omega)\lambda + \pi_C(b,i_L)\omega(1-\lambda)}.
\end{aligned}$$

Under assumptions 3.1 and 3.2, each of these probabilities is decreasing in i.[12] Thus, the proportion of firms with an A or C rating and an H or L signal that are g-type will be lower if firms increase i. Conversely, the proportion that are b-type will be higher.

As the pool of firms with an A or C rating and v signal now contains proportionately less type g and more type b firms, the expected default rate of the pool will increase. The corresponding change in the interest rate is:

$$\frac{\partial \mathrm{R}^*(\kappa,H)}{\partial i_v^*} = \frac{r\omega\lambda(1-\omega)(1-\lambda)[\pi_\kappa(G,i_v^*)\pi_\kappa'(b) - \pi_\kappa(B,i_v^*)\pi_\kappa'(g)](\gamma_g-\gamma_b)}{(\Pr(g,v,\kappa|i_v^*)\gamma_g + \Pr(B,v,\kappa|i_v^*)\gamma_b)^2}, \tag{3.10}$$

where $\pi_\kappa(\theta,i)$ is the probability of receiving rating κ at type θ and investment i, and $\pi_\kappa'(\theta)$ is the derivative of π_κ with respect to i. This expression is positive, indicating that $\mathrm{R}^*(\kappa|v)$ is increasing in i_v^* for κ equal to A or C.[13] The interest rate increases because the proportion of type g firms is decreasing (and thus that of b types is increasing) in the pool of A or C-rated, v-signal firms. So, a random A or C-rated, v-signal firm is now more likely to be b type and the default rate of firms in this pool has increased.

As the interest rate increases, so does the borrowing cost. The net return to the project for the firm, $y-R$, is therefore lowered, along with the marginal benefit of investment in ratings. The change in the marginal benefit is:

$$\frac{\partial \mathrm{MB}_H(\mathbf{R}^*)}{\partial \mathrm{R}^*(\kappa|v)} = \sum_{\kappa=A,C} -\frac{\omega\lambda\pi_\kappa'(g)\gamma_g + (1-\omega)(1-\lambda)\pi_\kappa'(b)\gamma_b}{\omega\lambda + (1-\omega)(1-\lambda)} \tag{3.11}$$

$$\frac{\partial \mathrm{MB}_L(\mathbf{R}^*)}{\partial \mathrm{R}^*(\kappa|v)} = \sum_{\kappa=A,C} -\frac{(1-\omega)\lambda\pi_\kappa'(g)\gamma_g + \omega(1-\lambda)\pi_\kappa'(b)\gamma_b}{(1-\omega)\lambda + \omega(1-\lambda)} \tag{3.12}$$

Note that the interest rate for B rated firms, $\mathrm{R}^*(B,v)$, does not change with i_v^* and therefore has

[12]See Appendix B.2.

[13]This is true as $\frac{\pi_\kappa'(g)}{\pi_\kappa(g,i_v)} < \frac{\pi_\kappa'(b)}{\pi_\kappa(b,i_v)}$ for $\kappa \epsilon \{A,C\}$ (which holds whenever $\sigma_1^g > 0$ and $\sigma_1^b > 0$ (see Appendix B.2)) and $\gamma_g > \gamma_b$.

no bearing on the marginal benefit.[14] As the marginal benefit decreases, an individual firm would like to *decrease* their investment in the ratings process, as $i_v^* = \mathrm{MB}_H(\mathbf{R}^*)^{\frac{1}{\alpha-1}}$. This is a contradiction.

Proposition 3.4.1 states that when the public signal becomes more accurate, firms that receive both the H and L signal will decrease their investment in the ratings process. The result implies that the number of firms that receive an A rating will decrease, *conditional on a public signal.* This is clearly a strong indication that the unconditional number of firms that receive an A rating will decrease. However, it remains to show that this is indeed the case as an increase in ω will also affect the distribution of public signals. Proposition 3.4.2 characterizes the conditions that ensure the effect of decreased investment in ratings dominates any distributional effect.

Proposition 3.4.2 *Consider ω_1, ω_2. Let $\mu_j(\kappa)$ be the measure of firms rated κ if $\omega = \omega_j$. Then, for any $\omega_1 < \omega_2$,*

$$\mu_1(A) > \mu_2(A), \mu_1(B) < \mu_2(B), \text{ and } \mu_1(C) < \mu_2(C).$$

if

$$i_H > i_L \text{ and } \lambda < \frac{\pi'_\kappa(b)}{\pi'_\kappa(g) + \pi'_\kappa(b)}$$

$$\text{or}$$

$$i_H < i_L \text{ and } \lambda > \frac{\pi'_\kappa(b)}{\pi'_\kappa(g) + \pi'_\kappa(b)}.$$

Proof Let $i_v(\omega)$ be the investment chosen by firms with signal v if the public signal accuracy is ω. By Proposition (3.4.1), $i_v(\omega_1) > i_v(\omega_2)$ for any $\omega_1 < \omega_2$. As $\pi_\kappa(\theta, i_v)$ is increasing in i for $\kappa = A$ and decreasing in i for $\kappa = B, C$, it follows that $\pi_A(\theta, i_v(\omega_1)) > \pi_A(\theta, i_v(\omega_2))$, $\pi_B(\theta, i_v(\omega_1)) < \pi_B(\theta, i_v(\omega_2))$, and $\pi_C(\theta, i_v(\omega_1)) < \pi_C(\theta, i_v(\omega_2))$.

By the law of total probability, the measure of firms with rating κ is:

$$\mu(\kappa) = \sum_\theta \sum_v \Pr(\kappa|\theta, v)\Pr(v|\theta)\Pr(\theta). \tag{3.13}$$

As ω increases there are two effects. The first effect is due to the decrease in i articulated above, which changes the rating probabilities conditional on each public signal. The second effect is due to the change in the distribution of H and L signals, conditional of firm type, θ. As ω increases, the probability that a g-type (b-type) firm will receive signal H (L) is larger, and

[14] In contrast to the relevant condition for A or C, $\frac{\pi'_B(g)}{\pi_B(g, i_v)} = \frac{\pi'_B(b)}{\pi_B(b, i_v)}$.

conversely the probability that a g-type (b-type) firm will receive signal L (H) is smaller. As can be seen in Equation (3.13), these probabilities weight each term of the summation. Thus, both effects must be taken into account to determine the change in the ratings distribution that is caused by ω.

Taking the derivative of Equation (3.13) with respect to ω results in the following expression:

$$\begin{aligned}\frac{d\mu(\kappa)}{d\omega} =& \Big(\pi'_{\kappa}(g)\lambda - \pi'_{\kappa}(b)(1-\lambda)\Big)(i_H - i_L) \\ &+ \pi'_{\kappa}(g)\lambda\Big(\omega\frac{\partial i_H}{\partial\omega} + (1-\omega)\frac{\partial i_L}{\partial\omega}\Big) \\ &+ \pi'_{\kappa}(b)(1-\lambda)\Big((1-\omega)\frac{\partial i_H}{\partial\omega} + \omega\frac{\partial i_L}{\partial\omega}\Big). \end{aligned} \tag{3.14}$$

Recall that $\frac{\partial i_H}{\partial\omega}$ and $\frac{\partial i_L}{\partial\omega}$ are negative. This implies that the second and third terms of Equation (3.14) are both negative (positive) if $\pi'_{\kappa}(\theta)$ is positive (negative), as is the case for firms rated A (B, C). Finally, $\mu(A)$ ($\mu(B), \mu(C)$) is decreasing (increasing) in ω if either of the following conditions hold:

$$i_H > i_L \text{ and } \lambda < \frac{\pi'_{\kappa}(b)}{\pi'_{\kappa}(g) + \pi'_{\kappa}(b)}$$

or

$$i_H < i_L \text{ and } \lambda > \frac{\pi'_{\kappa}(b)}{\pi'_{\kappa}(g) + \pi'_{\kappa}(b)}.$$

These conditions ensure that the change in the composition of signal-type pairs does not dominate the change in the probability that each signal-type pair receives a given rating.[15]

The intuition for this result is straightforward. As all firms decrease their investment in the ratings process when ω increases, the probability that a firm with either public signal receives an A rating is decreasing, while the probability they receive a B or C rating is increasing. Provided the indirect effect of the change in the distribution of signal-type pairs due the increase in ω does not dominate the direct effect of the ratings change, the distribution of ratings will evolve as described.

As interest rates or bond prices directly reflect the information available to the market, it is natural to consider the implications of an increase in the accuracy of public information on this front. Proposition (3.4.3) states that, as the public signal becomes more accurate, the dispersion of bond prices within a rating category will increase. This is because investors are more sure

[15] Note that these are sufficient, but not necessary, conditions. Weaker conditions are easily obtainable, but lack any immediate economic interpretation.

that a firm that receives a H signal is a g-type firm, and also more sure that those with a L signal are b-types. The difference in interest rates will increase to reflect this.

Proposition 3.4.3 *Consider ω_1, ω_2. Let $R_j(A, v)$ be the equilibrium interest rate for firms rated A with signal v when $\omega = \omega_j$. Then, for any $\omega_1 < \omega_2$,*

$$R_1(A, L) - R_1(A, H) < R_2(A, L) - R_2(A, H).$$

Proof The proof only requires showing that $R^*(A, H)$ decreasing in ω and $R^*(A, L)$ increasing in ω. Therefore $R^*(A, L) - R^*(A, H)$ increasing in ω. See Appendix B.2.

3.5 The Variation of Bond Spreads

The implication of Proposition 3.4.3 is that the dispersion of interest rates within a rating class is increasing. To confirm this in the data, I use the *Mergent Fixed Income Securities Database*. This is a comprehensive database of publicly-offered U.S. bonds. All of the information about the bonds themselves is sourced from bond prospectus while the ratings and CUSIP data are obtained directly from the source.[16] The linked issuer and issue data covers 77% of U.S. firms. Furthermore, the ratings data includes ratings from the 4 major credit rating agencies (Standard & Poor's, Moody's, Fitch, and Duff&Phelps).

Due to the low number of AAA-rated firms (and therefore bond issues from these firms) I use 4 year bins, starting in 1990. I take the yield to maturity spread over Treasury bonds matched by maturity at the offering date. Following the literature, I use the spread over treasury bonds as this measures the risk and default premium, which is germane to the analysis.[17] I restrict the sample to fixed coupon bonds for consistency in the yield to maturity calculation, which eliminates at most 1% of the observations in a given year. To match the sample used in the analysis of the ratings distribution change, I further restrict the sample by omitting firms in the financial sector, though there are many. The resulting sample is summarized in Table 3.2.

To document the pattern implied by Proposition 3.4.3 in the data, I plot the distribution of interest rate spreads over treasury for each rating class and further split the sample into an "early" (1990s) and "late" (2000s) time period in Figures 3.6, 3.7 and 3.8. The dispersion of bond spreads does seem to be increasing in the two investment-grade classes (AAA or AA and A or BBB), especially so for the high investment-grade class.

[16] CUSIP is the Committee on Uniform Security Identification Procedures, used to identify securities and issuers.

[17] There is also a tax premium in the price of corporate bonds as interest payments on these bonds are taxed at the state level, while interest payments on government bonds are not. See Elton, Gruber, Agrawal & Mann (2001).

Table 3.2: Observations in each rating-period bin

Ratings	1990-93	1994-97	1998-2001	2002-05	2006-09	Total
All	1,080	1,624	2,422	2,071	1,551	8,748
AAA/AA	223	228	287	134	91	963
A/BBB	719	980	1,346	866	902	4,813
SG	138	416	789	1,071	558	2,972

One concern is that the increasing dispersion is simply caused by an increasing mean, as one consequence of this is an increase in the standard deviation. As the coefficient of variation is immune to these perturbations it is more suited for this analysis. Therefore, to further substantiate the aforementioned pattern I calculate the coefficient of variation for each rating class and period as defined in Table 3.2. I construct 95% confidence intervals to determine whether any change in the coefficient of variation is statistically significant. The method used to construct the confidence intervals can be found in Appendix B.1. The result of this approach can be seen in Figure 3.9. There is a large, statistically significant, increase in the coefficient of variation over the sample period in both the AAA and AA (which increased by 56%) and the A and BBB (29%) rating classes. Curiously, there is also a statistically significant decrease in the speculative grade rating class (26%), though this disappears by the end of the sample period.

3.6 Discussion

In the wake of the 2007-2009 financial crisis, previous efforts to regulate capital markets have been questioned. A significant part of this scrutiny has been directed towards credit rating agencies (CRAs) and their role in mispricing risk. Though CRA behaviour has been studied in the context of other asset markets, the corporate bond market has been neglected. This paper is a step towards understanding the corporate bond market, specifically how firms behave when investors use both credit ratings and public information to make investment decisions and price bonds.

As public information has proliferated, its usefulness to investors has increased. Investors can now place more weight on this information as they evaluate firms. It is costly for firms to comply with the requirements of the CRAs as they improve their rating, whereas public information is provided without cost. Thus, firms are able to convey their creditworthiness at a reduced cost if investors use relatively more public information to make their investment decisions and if the market price of their debt is determined in part by both credit ratings and public information.

I construct a model that captures the role of credit ratings and public information in the cor-

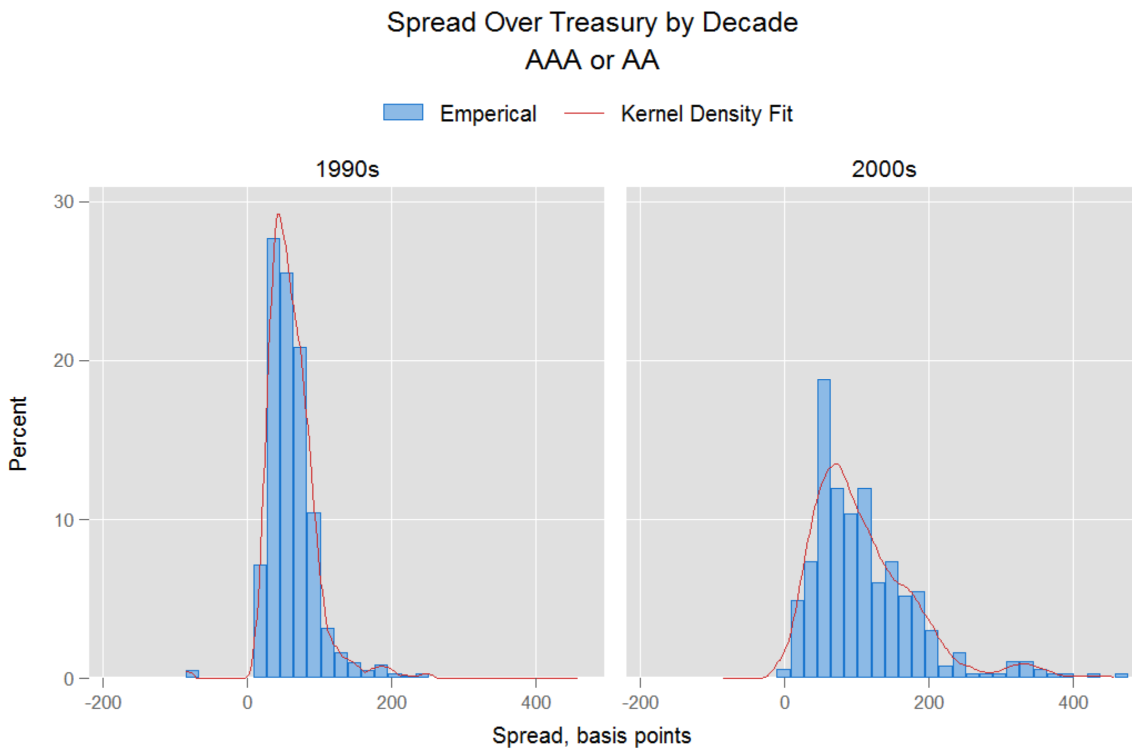

Figure 3.6: Spread over Treasury for AAA and AA bonds.

porate bond market to provide an explanation of the ratings distribution shift. Proposition 3.4.1 states that firms will devote less resources to improving their credit rating as public information proliferates. This leads to the main result of the paper, Proposition 3.4.2, which shows that the number of firms with the highest rating will decrease, while the number of firms with mediocre and low ratings increase, when information proliferates. Thus, the change in the rating distribution of the model matches that in the data, lending credence to proposed mechanism.

The shift in the credit ratings distribution is drastic. There has been a 70% decrease in the number of AAA or AA-rated firms, while the number of A or BBB-rated firms has increased by 77% and the number issuing speculative debt has increased by 129%. This stark shift away from the top ratings towards the lower end of the rating distribution cannot be explained by changes in the leverage ratios of firms, nor can it be explained by mergers or changing CRA standards.

Proposition 3.4.3 states that, as the accuracy of public information increases, so too will the dispersion of interest rates within a rating group. The intuition for this result is straightforward: as investors now learn more about firms through public information they are able more accurately price debt above the accuracy provided by credit ratings. Using new data, I show that this is indeed the case for investment grade debt over the last 20 years. The coefficient of

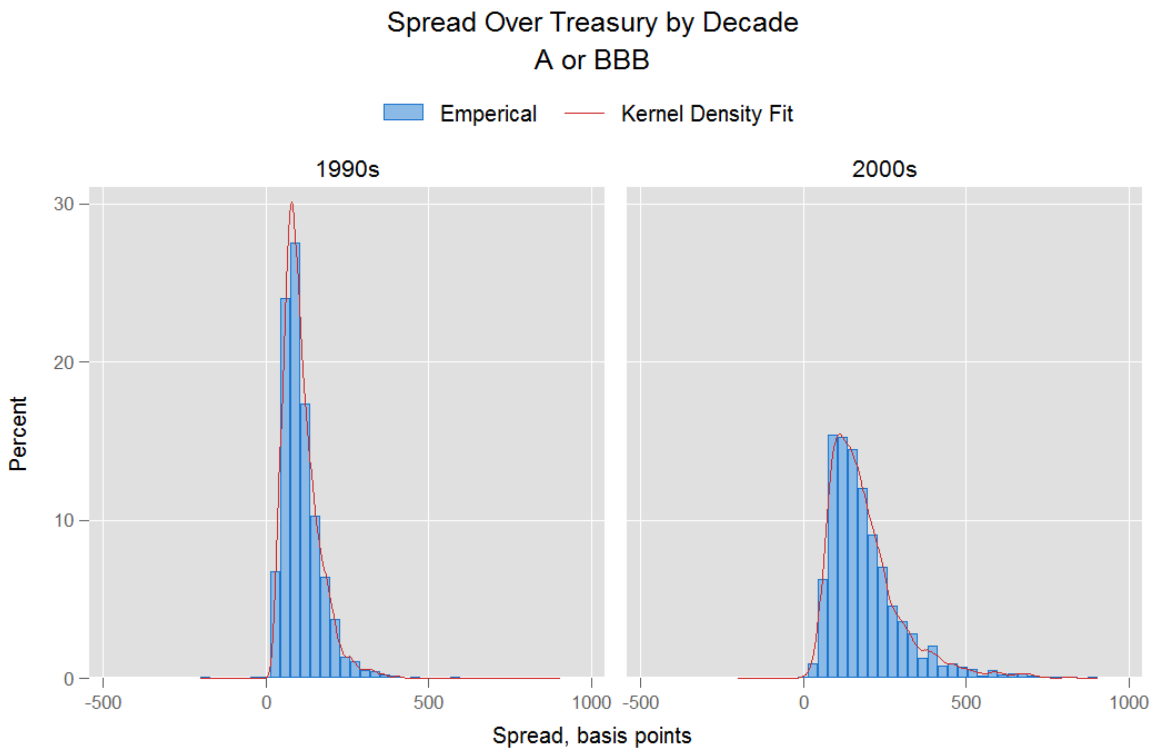

Figure 3.7: Spread over Treasury for A and BBB bonds.

variation has increased by 56% for AAA or AA-rated debt and by 29% for A or BBB-rated debt. This dramatic increase in price dispersion is previously undocumented.

As certain large investors are required to purchase highly rated debt or have lower capital requirements for investment grade debt holdings (as opposed to speculative), it is necessary for many firms to attain an investment grade credit rating to gain access to this segment of the market. Firms can also comply with CRA standards to improve their rating as this will lower their borrowing costs. This is costly, however, and as public information has become more reliable firms need no longer improve their credit rating to lower their borrowing cost.

Understanding how firms use credit ratings is important as regulation of the credit rating agencies has become a pressing policy issue following the financial crisis of 2007-2009. To this point, the Dodd-Frank Act mandates the creation of an Office of Credit Ratings to enhance regulation of these agencies.[18] Much of this enhanced regulation will increase the bureaucratic burden of issuing a rating, the cost of which may be passed on to firms. If this comes to pass, my research suggests that firms will devote fewer resources to ratings, further lowering the reliability of credit ratings.

Recognizing this behaviour is integral to understanding capital markets. Regulatory chan-

[18]The official name of this act is ‘The Dodd-Frank Wall Street Reform and Consumer Protection Act.’

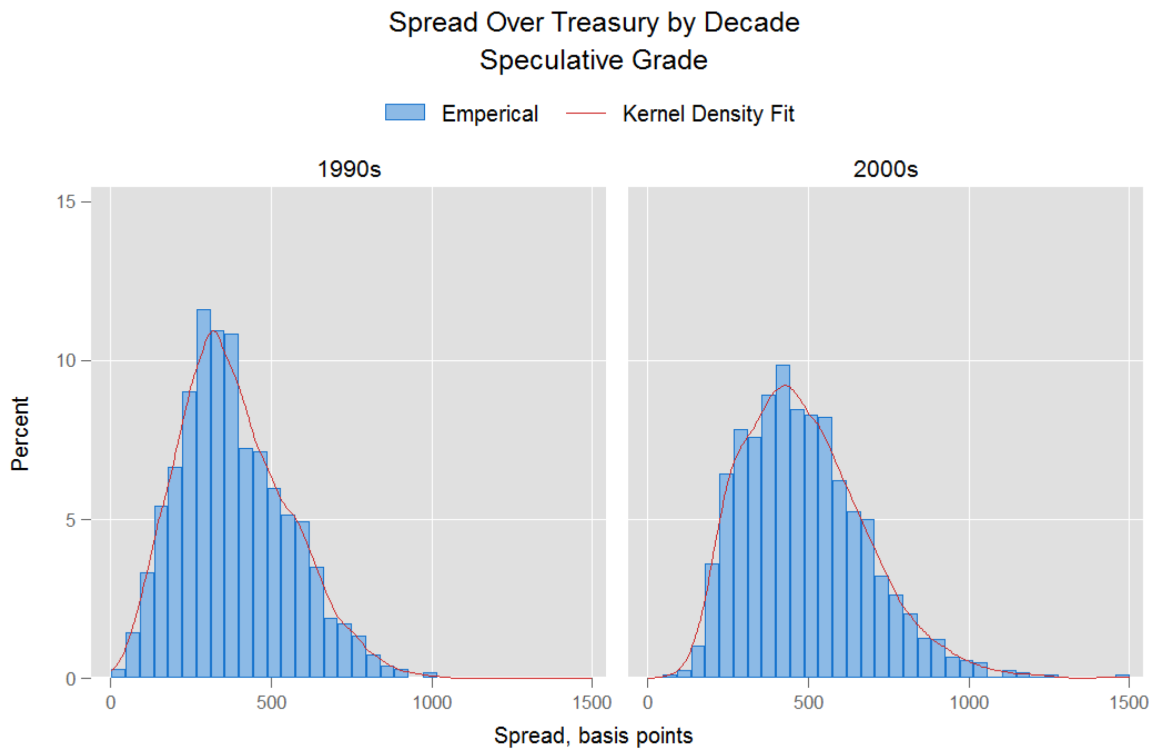

Figure 3.8: Spread over Treasury for BBB or lower bonds.

ges, such as the Dodd-Frank Act, which do not take this channel into account risk being ineffective, or worse, counter-productive. Also, the credit rating distribution is used by some as a measure of the aggregate riskiness of firms in the economy. In this paper I show that firms need not be riskier for the ratings distribution to shift towards lower ratings.

3.7 Conclusion

This paper in part seeks to answer the question: "Why are the highly rated firms disappearing?" The change in the distribution of firm ratings has been dramatic and has not thus far been documented in the academic literature. Possible explanations for this pattern, such as evolving credit rating agency standards, more highly levered firms, and firms merging, are explored and rejected.

Instead I propose a mechanism that captures the increase in the proliferation of firm information. Investors no longer rely solely on credit ratings to relay firm information and firms need no longer devote resources to unproductive ratings activities. Thus the demand for high ratings is lessened from both investors and firms, a story consistent with the changes purported by the financial press. However, due to regulations that require certain types of investors to

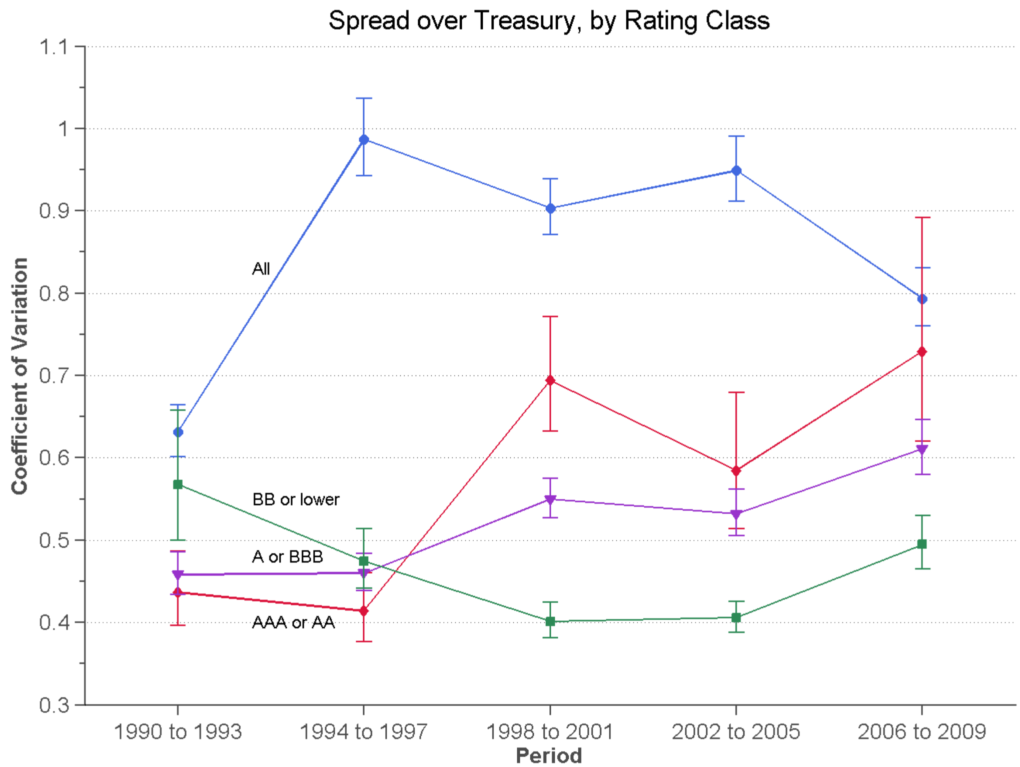

Figure 3.9: Coefficient of variation with 95% confidence intervals, by rating class.

hold only investment grade assets, credit ratings retain a certain value. Considering this, it is the value of the highest ratings relative to other investment grade ratings that has diminished.

Chapter 4

Consumption Insurance with Endogenously Segmented Markets

4.1 Introduction

The household consumption-savings decision and consumption inequality have been important areas of research in economics, but some aspects remain unexplored to their full extent. In particular, I focus on the different level of access that households have to financial markets, the effect this has on household savings and investment, and what this means for consumption inequality. In this paper, differential access is caused by costs which are not proportional to income and thus cause heterogeneous behaviour across income levels. The motivation for this study comes from, in part, the empirical rejection of perfect risk sharing, i.e., that households are able to insure against all idiosyncratic shocks.[1] By adding a fixed cost for market participation, I show that the model exhibits the desired degree of risk sharing by controlling access on the *extensive* margin, while allowing income-rich households full consumption insurance. This further restricts the degree of risk sharing relative to the debt constraint models (discussed below) on an aggregate level. From a theoretical standpoint, the benefit of this fixed cost is that the market segmentation is *endogenous* and thus households can pay for access at any point in their lifetime.

The model of Endogenously Segmented Markets (ESM) developed herein exhibits a mixture of perfect risk sharing and no risk sharing in different segments of the economy. In order to justify such a model, there should be evidence of two features: heterogeneous market participation and a fixed cost for access. The former can be seen in the high concentration of asset holdings and wealth in the upper portion of the income distribution. Wolff (2010) finds that the

[1]See, for example, Attanasio & Davis (1996) who show that the standard Arrow-Debreu complete markets model cannot explain the joint distribution of earnings and consumption in U.S. cross-sectional data.

top quintile by income holds 44% of their net worth in real estate, business equity, stock and bonds compared to 14% for the middle 3 quintiles in the *Survey of Consumer Finances* (SCF) in 2007. Furthermore, the author finds that 55% of the total value of life insurance is held by the top 10%. Studying the same sample, Guvenen (2007a) finds that 90% of non-housing wealth and 98% of stocks are owned by the richest 20% of the U.S. population by income. By most measures, the distribution of assets is heavily skewed to the left.

A fixed cost for access is not so easily observed. Following Guvenen (2007a), it is meant to capture both implicit and explicit costs endured by those who trade in financial markets. These would include time and effort costs of tasks that include filing a more complicated tax return, membership or access costs to internet trading houses, brokerage fees that aren't "per trade" and costs of information acquisition. Vissing-Jørgensen (2002) finds that modest costs ($50 to $260) are enough to explain the decision of most non-participants in the stock market.

The basic models on household consumption and savings fall into two classes. The first are the incomplete market models such as Aiyagari (1994) or Huggett (1993) in which infinitely-lived households use "precautionary savings" to smooth their consumption. More recently, Storesletten, Telmer & Yaron (2004) use the same framework in a life-cycle model. Though this market structure is useful as a lower bound for the asset set of an entire economy, there are clearly more opportunities to smooth consumption (such as disability insurance and other financial instruments). Saving with a single bond is arguably a more apt description of low-income household behaviour, as this group rarely holds their wealth in assets other than their primary residence. This can be seen in the SCF where households with income under $15,000 in 2007 make up 13.3% of households but hold only 1.2% of total stock holdings, either indirectly or directly. In the *Panel Study of Income Dynamics* (PSID), the asset income of households that earn more than $30,000 is over three times that of those that earn less than $30,000. The second class of models, such as the model studied in Kehoe & Levine (1993), restrict asset purchases in a more natural manner: debt constraints. In these models a household (or an agent) cannot commit to paying back any amount of debt which would make autarky more appealing, though they have access to assets which span the state space. In this sense, risk sharing is restricted on the intensive margin, i.e., households cannot borrow or lend as much as they wish but may purchase assets for every state.[2]

Krueger & Perri (2006) determine that the degree of risk sharing in the economy would seem to be in between that of a simple bond economy (incomplete markets) and an economy with limited commitment (restricted complete markets). The authors come to this conclusion as the increase in consumption variance from 1980 to 2004, as measured in the *Consumer*

[2] Kocherlakota (1996) shows that complete risk sharing is in fact possible in this environment if agents are sufficiently patient.

Expenditure Survey (CEX), is lower than that predicted by a bond economy and higher than that predicted by a debt-constrained economy.[3] It may be, however, that each of the basic models accurately describes a certain *segment* of the economy, while inaccurately describing the economy as a whole. As mentioned above, the single bond economy seems to suitably describe the behaviour of low-income households, while the observed wealth holdings of high-income households indicates that they have access to a wider class of assets.

It is important to study economic inequality as it bears directly on policy concerns such as education and social security. Most of the existing literature has focused on the inequality of income or wealth and ignored, to a certain degree, the inequality of consumption. This is surprising as consumption, not income or wealth, is included in the household objective function and thus it should be of primary concern. A recent paper by Heathcoate, Perri & Violante (2010) documents the change in economic inequality in the United States by examining changes in the variance of wages, hours worked, income, earnings and consumption. The authors find that the increase in consumption inequality is less than that of income inequality and suggest that this implies some part of the income process is insurable, but not all.[4] This is only true if, in response to rising income variance, all households behave in a similar fashion which I argue is not the case. The main result of this paper is that the observed increase in consumption inequality misrepresents the true welfare effect of an increase in income variance. This is because the increase in income variance has two effects on the unconditional variance of log consumption: (1) an increase in group risk sharing for high income households (as group market participation increases), resulting in lower consumption variance; and (2) a direct increase in consumption variance for low income households, as the fixed cost is more restrictive and market participation does not increase.

To further develop the ESM model, I examine the effects of a change in the persistence of income shocks. An increase in persistence will decrease the risk faced by a household, as it is subject to fewer shocks but will also increase the difference in lifetime utility caused by a high or low income shock. The model predicts a decrease in market participation when persistence is raised, suggesting that in this environment the former effect is more important for household welfare. Finally, I show that when the financial markets are interpreted as traditional insurance markets (such as for disability or life insurance), the ESM model supports two empirical observations which are seemingly opposed: namely, the negative correlation between *income* and insurance purchases and the positive correlation between *wealth* and insurance purcha-

[3] I refer to the within-group (log of) consumption variance. The between-group variance is lower in the data than both of the basic models. The within-group variance is of more interest as it reflects the level of risk sharing in the economy.

[4] The authors also confirm that the samples used by the PSID, CEX and CPS are comparable, lending justification to the use of income and consumption data from the different surveys in the same study.

ses. The intuition is that wealth is used for precautionary savings which become redundant for households that can afford the fixed cost of market participation.

Recently there have been empirical studies attempting to measure the degree of risk sharing while accounting for different household characteristics. Blundell, Pistaferri & Preston (2008) estimate an income process from PSID data and consumption demand functions from CEX data and find evidence for higher risk sharing amongst the college educated and older generations. Guvenen (2007a) finds empirical evidence in the PSID for perfect risk-sharing amongst non-stockholders but rejects perfect risk sharing for stockholders, who are generally more wealthy. Gervais & Klein (2010) confirm this result though they find that "the degree of risk sharing is nevertheless quite high." As clarification, Narita & Narita (2009), who construct a synthetic panel from the CEX, find that, though stockholders face more consumption risk than do non-stockholders, they are able to insure a greater proportion of their total risk. These results suggest that certain household characteristics allow it different consumption insurance opportunities and that a model which incorporates these features is more suited to describing the effects of inequality.

The rest of the paper is organized as follows. The model, income process and equilibrium concept are discussed in Section 2. Results are provided in Section 3. Section 4 concludes and discusses potential directions for future work.

4.2 Model

4.2.1 Environment

The environment is populated by a finite number of households, each of which lives for T discrete periods. Households derive utility from consumption and discount future utility by a factor β. The lifetime utility of a household is represented by

$$U^i(\boldsymbol{c}^i) = E_0\Big[\sum_{j=1}^{T}\beta^j u(c^i_j)\Big], \tag{4.1}$$

where c^i_j is consumption at age j for household i and $\boldsymbol{c}^i = \left\{c^i_j\right\}_{j=1}^{T}$. The contemporaneous utility function, u, is assumed to be continuously differentiable and concave.

The uncertainty in the model arises through fluctuations in each household's income, $y^i_{j,t}(s_t) = X^i_j w(s_t)$, where X^i_j reflects the household's age and type[5] and $w(s_t)$ are the wages at s_t, the state-

[5]This heterogeneity is meant to capture fixed characteristics that would affect a household's income, such as education level, and the life-cycle of income.

event pair.[6] Let $s^{i,j,t}$ denote the history of realized states from age 1 through j for household i born at time t and s^t the history of realized states for all households. Each s_t is drawn from the set S of all possible states, thus $s^{i,j,t} \epsilon S^j$ and $s^t \epsilon S^t$. As the birth period does not vary over the household's lifetime, I suppress this in the notation for simplicity and rewrite $s^{i,j,t}$ as $s^{i,j}$. The lifetime utility of each household can then be rewritten as

$$U^i(\boldsymbol{c}^i) = \sum_{j=1}^{T} \sum_{s_j \epsilon S} \beta^j \pi(s_j | s^{i,j-1}) u(c^i_j(s_j | s^{i,j-1})), \tag{4.2}$$

where $\pi(s_j|s^{i,j-1})$ is the probability of realizing state s_j given the history $s^{i,j-1}$.

Financial Markets

Certain households have access to markets in which they may purchase one-period Arrow securities, all of which pay one unit of consumption in a single state. These securities span the state space. To gain access to these markets, households must pay a fixed cost, η, within every period that they wish to purchase these state-contingent assets. For instance, a household could pay η to purchase Arrow securities at time t which then mature at time $t+1$, and could pay η again at time $t+1$ for the right to purchase securities that mature at time $t+2$. All households may trade risk-free bonds in every period. There is full commitment for both complete and incomplete markets.

Household Problem

The main household problem can be represented recursively by two separate problems: that of a household with and without access to complete markets (and thus perfect insurance). Let $q(s_{t+1}|s^t)$ be the price of a security given history s_t and $q_0(s_t)$ be the price of a bond. Denote $\boldsymbol{a}^{i,j}_{j+1}$ as the vector of security holdings and $b^{i,j}_{j+1}$ as the bond holdings for household i at age j the payoffs for which are realized in $j+1$. The problem of a household with access is then

$$\begin{aligned} V_{in}(j, s, \boldsymbol{a}, b) = \max \Big\{ & \max_{\boldsymbol{a}', b'} u(c) + \beta E[V_{in}(j+1, s', \boldsymbol{a}', b')|s], \\ & \max_{\boldsymbol{a}', b'} u(c) + \beta E[V_{out}(j+1, s', \boldsymbol{a}', b')|s] \Big\} \end{aligned} \tag{4.3}$$

subject to

$$c + \sum_{s'} q(s'|s) a(s'|s^j) + q_0 b' + \eta \leq y(s^j) + b + a(s^j). \tag{4.4}$$

[6]The state contains the realization of uncertainty for all households at time t.

The problem of a household without access is

$$V_{out}(j, s, \boldsymbol{a}, b) = \max \left\{ \max_{b'} u(c) + \beta E[V_{in}(j+1, s', 0, b')|s], \right. \tag{4.5}$$
$$\left. \max_{b'} u(c) + \beta E[V_{out}(j+1, s', 0, b')|s] \right\}$$

subject to

$$c + q_0 b' \leq y(s^j) + b + a(s^j). \tag{4.6}$$

For ease of notation I have suppressed the time superscripts and subscripts and represent the state at time t and $t+1$ with s and s' respectively. Note that in (4.5) and (4.6) the household may still have non-zero holdings of the Arrow securities as access to complete markets may have been purchased in the previous period. The main household problem is simply the maximum of the two sub-problems:

$$V_{ESM}(j, s, \boldsymbol{a}, b) = \max \{V_{in}(j, s, \boldsymbol{a}, b), V_{out}(j, s, \boldsymbol{a}, b)\}. \tag{4.7}$$

This problem can be solved through backwards induction from age T using the appropriate terminal condition.

4.2.2 Equilibrium

The environment is analyzed as a small open economy. It is assumed that all of the trade in assets occurs between a household and a large financial industry so that both households and the supplier of the assets are price takers. As such, the sequence of prices, $\{(q(s_{t+1}|s^t))_{s_{t+1}\epsilon S}, q_0\}_{t=1}^{\infty}$ is set to be actuarially fair using a no arbitrage condition. Thus the prices are

$$q(s_{j+1}|s^j) = \frac{\pi(s_{j+1}|s^j)}{1+r}, q_0 = \frac{1}{1+r}. \tag{4.8}$$

This ensures that purchasing one unit of consumption *for sure* in the next period costs the same amount using either Arrow securities or bonds, as the sum of the security prices across all possible states in $t+1$ is equal to the price of the risk-free bond. An equilibrium is an allocation $\left\{(a^{i,j}(s_{j+1}|s^{i,j}))_{s_{j+1}\epsilon S}, b^i_{j+1}\right\}_{j=1}^{T}$ for every household i and prices as defined in (4.8) such that every household solves (4.7).

In general, a closed-form solution to the participation decision is not available. Note, however, that once market access is obtained a household is able to attain complete consumption insurance by equating the marginal utility of consumption in and across all histories:

$$u'(c(s_j|s^{j-1})) = u'(c(\bar{s}_j|s^{j-1})), \forall s_j, \bar{s}_j \epsilon S, \forall s^{j-1} \epsilon S^{j-1} \text{ for } j = 1, \dots, T, \tag{4.9}$$

$$u'(c(s_j|s^{j-1})) = u'(c(s_{j+1}|s^{j})), \forall s_j, s_{j+1} \epsilon S, \forall s^{j-1}, s^j \epsilon S^{j-1} \text{ for } j = 2, \dots, T-1. \tag{4.10}$$

Equations (4.9) and (4.10) are standard Euler equations. Households are thus guaranteed a constant consumption of $X\bar{w}$, where $\bar{w}$ is the average expected wage from the period after the household enters the complete markets agreement until T.

To further characterize the ESM model different steady states are compared. A steady state partial equilibrium has constant population weights, ω_i, which reflect the different possible household types, represented by values of X. Cohorts exist in equal number for a given household type. As I restrict entry into the complete markets agreement until the second period of a household's life, the fraction of households of a given type that could possibly have access is $\frac{T-1}{T}$. Thus I consider this fraction to be complete participation.

4.2.3 Income Process

Household earnings consist of a heterogenous part, X, and a stochastic idiosyncratic part, w. Thus, log earnings are:

$$\ln(y^i_{j,t}) = \ln(X^i_j) + \ln(w^i_j). \tag{4.11}$$

Define σ^2_X and σ^2_w as the between-group and within-group variance of log earnings, respectively. The value of X is permanent while shocks to w are transitory. Though X does not depend on time, it may depend on the household's age, which is indexed by j.

The values for the household-specific variable, X, are chosen to reflect the mean income for different levels of education, as specified in the Current Population Survey (CPS) for 2007. These values are then normalized to obtain a value relative to those who attain a college degree and no more. See Table 4.1 for the results. I construct the other portion of household earnings, w, as shocks that takes on the values $\pm\varepsilon_t$ with equal probability, independent of history.[7] The probabilities are then simply $\pi(s_{j+1}|s^j) = 0.5$ for all s_{j+1} and s^j. In order to determine the sequence of idiosyncratic income shocks I decompose the wages into a permanent and transitory part, as measured in the *Panel Study of Income Dynamics* (PSID). The method is identical to the 'moments in levels' method in Heathcoate, Perri and Violante (2010). As an increase in the magnitude of income shocks and different wage growth across skill cohorts would both generate the required increase in income variance, it is important to justify the use of income shocks. As argued in Storesletten, Telmer and Yaron (2004), differences in wage growth would

[7] The variance of w is $\frac{1}{2}(\ln(1-\varepsilon)^2 + \ln(1+\varepsilon)^2) - \frac{1}{4}(\ln(1-\varepsilon) + \ln(1+\varepsilon))^2$.

Table 4.1: Mean income by education level.

Education Level	Actual Income	Relative Income
<High School	21,484	0.541
High School	31,286	0.787
<College	33,009	0.830
College	39,746	1.000
Bachelor's	57,181	1.439
Master's	70,186	1.766
Doctorate	95,565	2.404
Professional	120,978	3.044

Source: Current Population Survey.

lead to constant changes in consumption inequality if households were able to borrow against future wage growth and wished to smooth consumption. Constant changes are not observed however, which lends credence to the use of income shocks.

I choose to vary the change in the persistent part of log earnings variance by changing the frequency at which households receive income shocks. High frequency shocks imply low persistence, and vice versa. Changing the persistence can affect the participation choice in two ways. First, under standard preference assumptions, the resulting difference in lifetime utility between *persistent* low and high shocks is greater than is the difference between purely *transient* low and high shocks, when these shocks are uninsured. Second, the household will see fewer shocks if persistence is high, thus reducing the uncertainty over a life cycle. The qualitative results of changing persistence will be shown below. In order to construct the life-cycle profile that I use to calibrate the model, I introduce income growth following Guvenen (2007b). He uses an annual linear growth rate of 0.07 for those who attain some college or less and 0.12 for those with a college degree of higher.

4.3 Results

To calibrate the ESM model I scale wage growth and cost of entry to match the life-cycle profile of log consumption variance in the CEX, as found in Deaton and Paxson (1994), at the median transitory income variance and with population weights for X.[8] This target for calibration is

[8]These weights are taken from the CPS and can be found in table 4.2.

Figure 4.1: Model calibration and estimated cross-sectional variance of log consumption.

Note: Data is the cross-sectional variance of log consumption from the CEX as generated by a cohort and age dummy variable regression. Model shows the result of the calibration. Source: Consumer Expenditure Survey.

used by both Guvenen (2007b) and Storesletten, Telmer and Yaron (2004).[9] To construct this profile I follow the method of Deaton and Paxson (1994) and run a dummy-variable regression on the variance of log (non-durable) consumption for each age-cohort pair. The age effects are then scaled so that the coefficients match the unconditional variance of a reference age group, on average (age 42 in this paper.) The scaled age dummy-variable coefficients and the profile generated by the model are plotted in figure 4.1. The discount rate β is set equal to $\frac{1}{1+r}$ where r is the annual interest rate which I choose to be 4%. The calibrated value of the fixed cost, η, is 0.006. Note that this value is of the same magnitude found by Vissing-Jørgensen (2002), when compared with the relative earnings in Table 4.1 as it translates to approximately $180.

The results of this calibration are then used to determine the degree of market participation for each household type at each level of income variance by resolving for the steady state. Figure 4.2 shows the degree of market participation for each household type at various levels

[9]The calibration results in an increase of 21 log-points in the model compared to a 20 log-point increase in the data. Guvenen (2007b) finds a 21 point increase, Storesletten, Telmer and Yaron (2004) find that the increase is 25 points and Deaton and Paxson (2004) also find a 25 point increase. Each paper uses the CEX sample from 1980 to 1990.

Table 4.2: Mean consumption and within-group log consumption variance, various values of ε.

Education Level	Population Weight	Consumption Mean,Variance Lowest ε μ_c	Lowest ε σ_w^2	Median ε μ_c	Median ε σ_w^2	Highest ε μ_c	Highest ε σ_w^2
<High School	12.50	0.57	0.17	0.57	0.20	0.57	0.23
High School	28.16	0.81	0.16	0.81	0.17	0.82	0.19
<College	18.53	0.86	0.15	0.86	0.17	0.86	0.18
College	8.10	1.03	0.14	1.03	0.16	1.03	0.17
Bachelor's	17.37	1.46	0.11	1.44	0.10	1.44	0.12
Master's	5.90	1.77	0.09	1.77	0.10	1.72	0.06
Doctorate	1.00	2.35	0.04	2.36	0.05	2.33	0.04
Professional	1.28	2.97	0.03	2.96	0.03	2.97	0.04

Source: Population weights from Current Population Survey.

of ε. Notice that as the transitory part of income variance increases it is the highly skilled households that enter the complete markets agreement. This is a reflection of the higher relative cost of entry facing the poorer households.

The change in market participation shown in Figure 4.2 demonstrates how the reaction to increased income variance differs across households, but does not account for the relative sizes of each type and so does not shed light on the aggregate change in market participation. In fact, though large fractions of a type may enter, the total participation never exceeds 20%.

Table 4.2 shows the chosen population weights, the within-group log consumption variance and the average consumption for different levels of ε. The largest changes in market access occur for the high-income types, a group which represent 26% of the total population (or a total weight of 24.27 using the type weights in Table 4.2). These are the only groups who see a reduction in their average consumption as a larger proportion of this group chooses to pay the fee for market entrance.

The remainder of the population, comprised of College, High School and less than High School, represent 72% of the population. For these groups, notice that the average consumption does not vary much even for large jumps in ϵ. Instead, the changes occur in the variance which rises significantly for each group. This is because the increased income variance does not cause increased market participation (for most households) and so no income is spent on entering the complete markets. Thus the increase in income variance is passed through to within-group consumption variance.

The measured consumption inequality increases over the period 1980-2004 discussed pre-

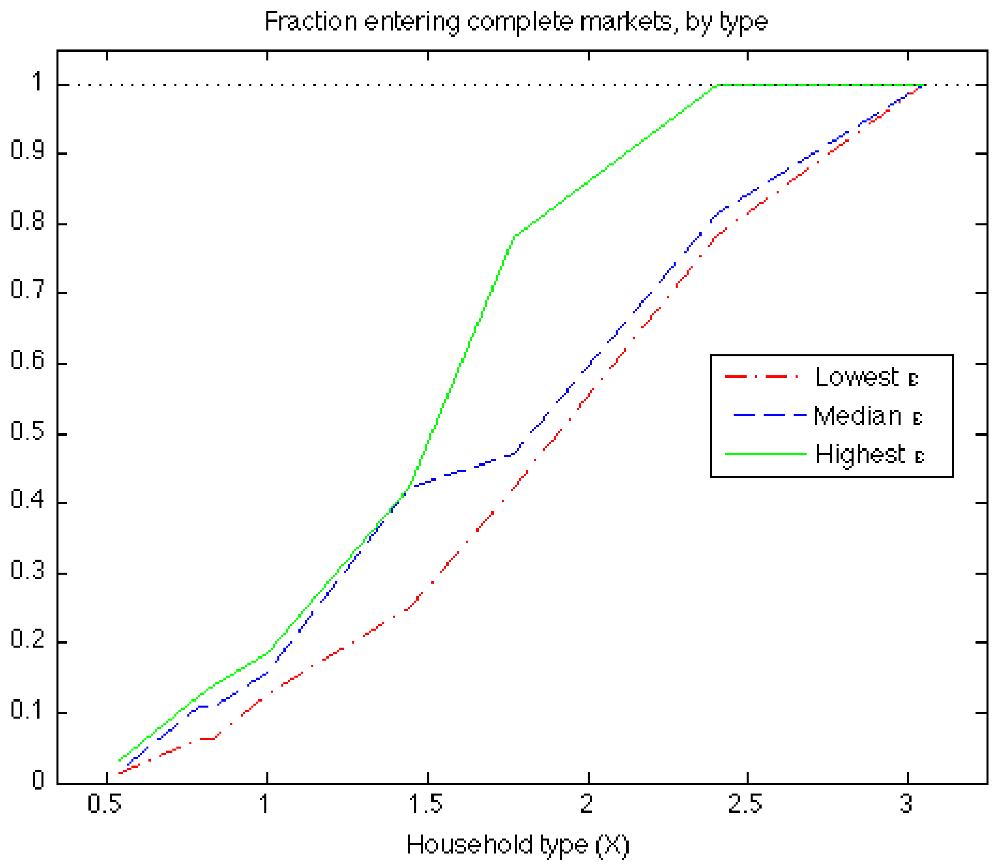

Figure 4.2: Fraction in complete markets, by type

viously are typically interpreted at the aggregate level. The results I find here suggest that this increase is primarily attributable to low-income households and aggregate changes bely the changes felt by low-income households. Researchers ignoring differences in market access caused by household income heterogeneity will fail to observe the full impact of increased income inequality as the increase in low-earner consumption inequality will be partially offset by the decrease in middle- and high-earner consumption inequality, as seen in Table 4.2.

4.3.1 Model Comparison

I now show that the ESM model can form a more accurate prediction of the consumption variance found by Krueger and Perri (2006) than the two basic models discussed in the introduction. To do this I set $\eta = \infty$ in (4.4) and re-simulate the model. This makes market participation unaffordable and effectively restricts the households to purchasing only the risk-free bond. With this change the model is equivalent to a simple incomplete markets (SIM) model.

The limited commitment complete markets model (LCCM) requires some explanation. First, I define the punishment for default as exclusion from the market for bonds and Arrow securities, or complete autarky, as is standard in the literature. I also impose a proportional penalty for default in period T.[10] The value of autarky is defined as:

$$V_{aut}(s) = u(c) + \beta E[V_{aut}(s')] \tag{4.12}$$

subject to

$$c \leq y(s). \tag{4.13}$$

Thus the household is subject to the full extent of the uncertainty in the earnings process. The individual rationality constraint requires that the value of participation is never less than the value of autarky. I can then define the the value of participation as (4.3) subject to (4.4) and the additional constraint

$$a^i(s_t) \geq A^i(s_t), \qquad \forall s_t \epsilon S, t = 1, \ldots, T.$$

$A^i(s_t)$ is determined numerically by the value of assets which makes the household indifferent between paying back $A^i(s_t)$ and permanently foregoing participation in securities markets. Without commitment, no household would rationally pay back any more as the value of default is greater than that of honouring their debt. Thus $\boldsymbol{A^i}$ solves

$$V^{LCCM}(s, \boldsymbol{A}, b) = V^{Aut}(s).$$

As in Krueger and Perri (2006), I solve for the efficient consumption allocations. These allocations provide maximum risk sharing while satisfying the individual rationality constraints. Agents with high income are awarded just enough to ensure they do not default and walk away from the agreement.

Recall that the SIM and LCCM models over- and understate, respectively, the degree of within-group consumption variance. Also, both models over-predict the between-group variance. In comparison to the SIM model, the ESM model predicts a lower degree of within-group consumption inequality, which increases at a lower rate. This is shown in Figure 4.3. Clearly, this is because only a fraction of the total population is limited to solely trading the risk-free bond in the ESM model, while the entire population is restricted to this bond in the SIM model. Also, the between-group consumption inequality is lower in the ESM than in the SIM model. Note that these series would be increasing if I included an upward trend for permanent income

[10] Including this penalty eliminates equilibria with no borrowing. This is because autarky is not a punishment for households in period T and if these households do not repay their debts, lending will unravel.

variance in the income process.

The LCCM model shows no upward trend in within-group consumption inequality and resides entirely below the variance predicted by the ESM model.[11] The relatively low variance reflects the fact that everyone is risk-sharing to a degree in this environment. These results suggest that endogenous segmentation is a factor that leads to differential insurance opportunities across households.

The next exercise attempts to determine whether increasing the persistence in the model encourages more participation in the complete markets agreement. This can be verified by decreasing the length of a period in the economy. If, for instance, the relevant portion of the lifecycle is roughly 40 years, the model period will determine how often a household is faced with a shock. The benchmark model is estimated using 5 periods, making each period 8 years long. Increasing the model period to 10 would change the period length to 4 years. Thus the households in the economy experience 5 more transient shocks to their income, which fully persist for 4 years instead of 8.[12]

I simulate the ESM model under the described changes and then again with a model period of 20 (which results in 20 shocks persisting for 2 years). The results can be seen in Figure 4.4. The environment with increased persistence shows decreased complete markets participation, indicating that the increased discrepancy between the continuation value after high and low shocks is a less important factor than is the increased uncertainty caused by more frequent shocks.

There is empirical evidence that insurance policy holdings are positively correlated with income and negatively correlated with wealth (see Beenstock et al. (1988) and Brown et al. (2000)). The ESM model supports both of these relationships, as shown by the correlations in Table 4.3. To see this consider Figures 4.5 and 4.6. The mean bond holdings for those with a college education or less (CL or less) and those with bachelor's degrees (BA, with mean income below \$60,000 in the CPS) are very similar. This is also true in the series for those earnings roughly \$70,000 (MA) until their bond holdings drop from 0.115 to 0.053, a change of 54%.

This dramatic change corresponds to a significant increase in complete market participation which offers the households full consumption insurance (against temporary shocks) seen in Figure 4.6 as the jump between the series for median and high variance. This jump also applies to the second highest class of earners (Doc) in Figure 4.5, a group which goes from high to total complete markets participation. Notice again that their bond holdings drop significantly

[11]Recall that the solution concept for the LCCM model was constrained efficiency, which determined the *maximum* degree of risk-sharing. Complete autarky is also an equilibrium in this environment. In that case the consumption variance would obviously be much higher.

[12]This formulation is supported by Storesletten et al. (2004) who find evidence for near unit-root persistence.

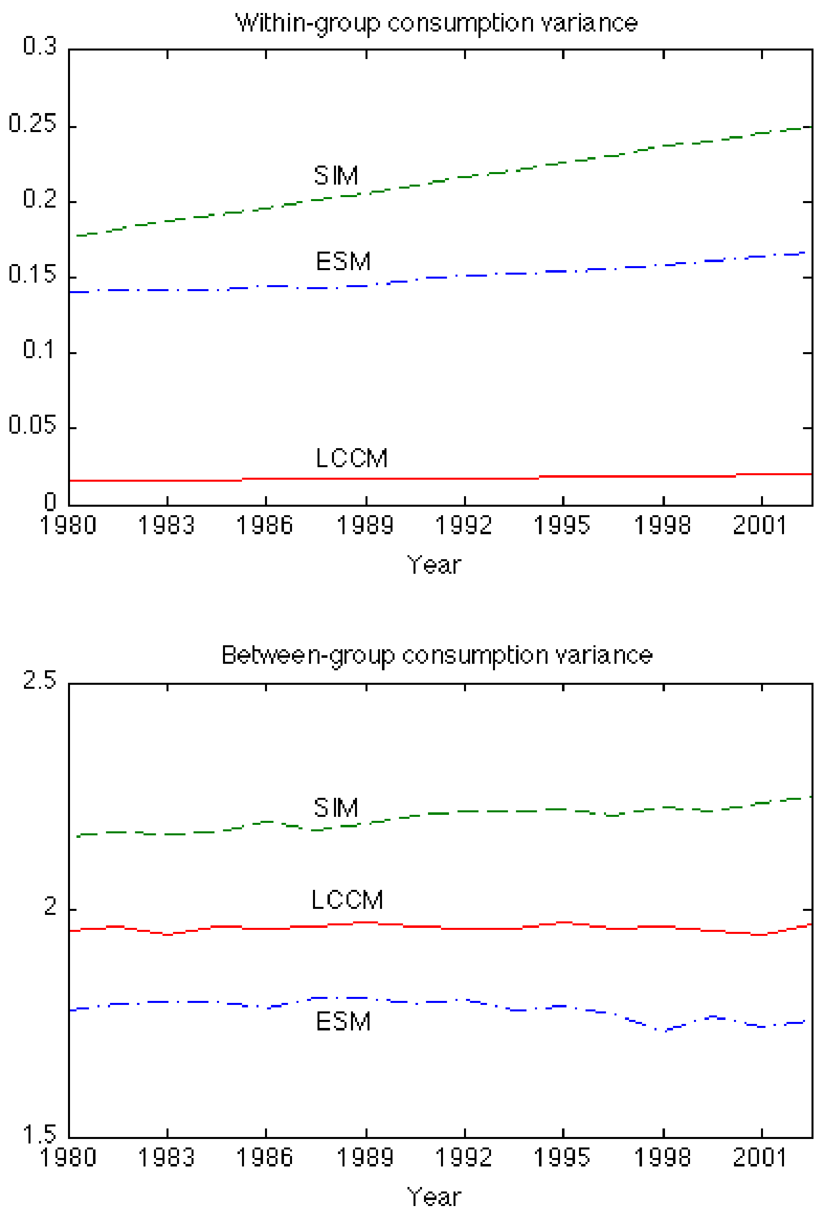

Figure 4.3: Within- and between-group variance of log-consumption

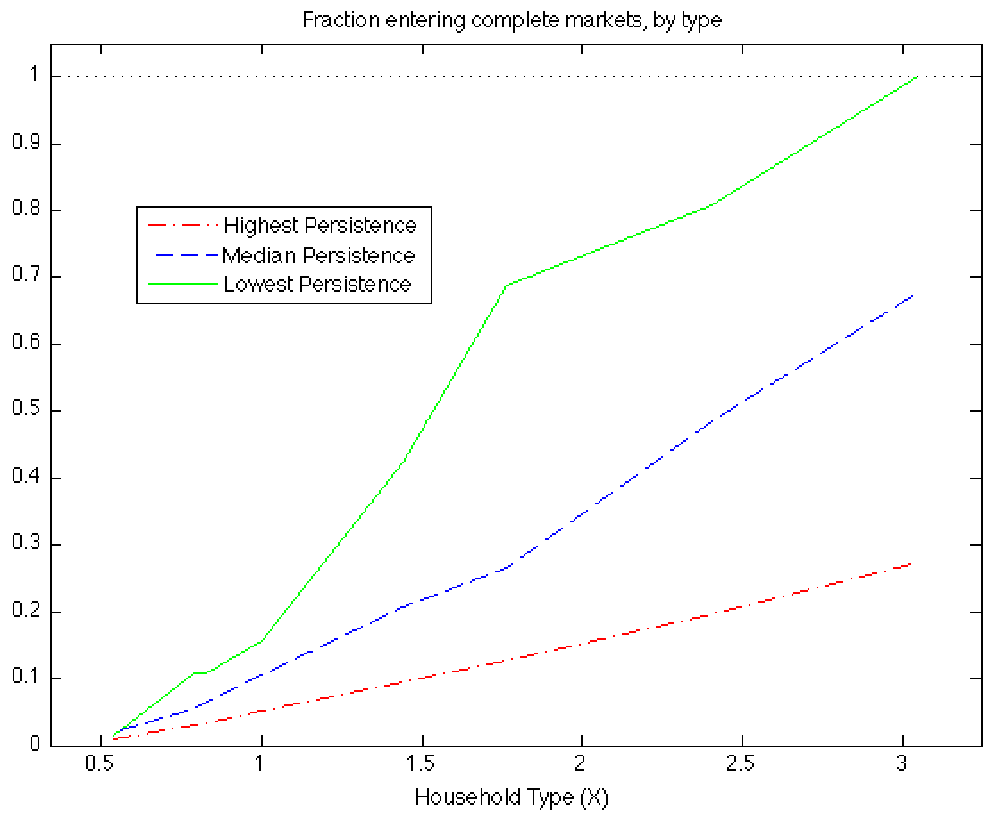

Figure 4.4: Fraction in complete markets, by type

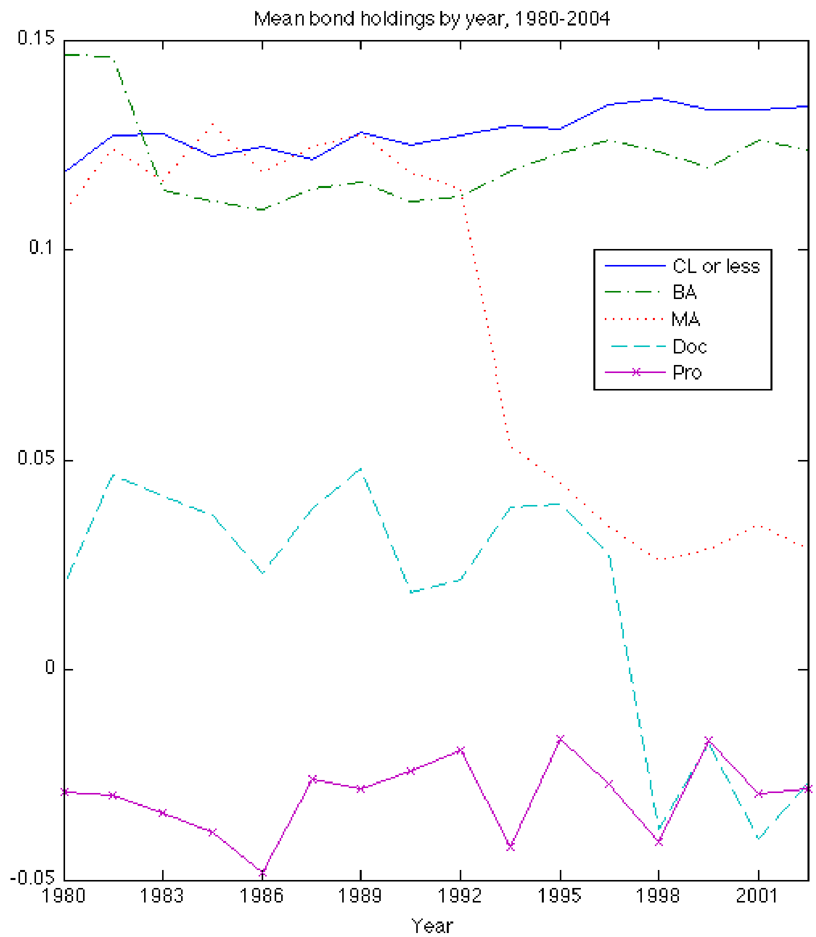

Figure 4.5: Mean bond holdings for each class, 1980-2004

Table 4.3: Simulated correlation between market participation and bonds holdings

Education Level	Correlation Coefficient	p-value
College or less	0.70	0.003
Bachelor's	-0.76	0.000
Master's	-0.99	0.000
Doctorate	-0.95	0.000
Professional	0.00	1.000

and are similar to that of the other group with total participation (Pro). So, bond holdings (or wealth) drop significantly as market participation increases, and those with higher incomes more frequently attain full consumption insurance by participating in the complete markets.

4.4 Conclusion

In this paper I studied the effect of a fixed cost for market participation on consumption variance. To calibrate the model, I match the age profile of the variance of log consumption as first reported in Deaton and Paxson (1994). This results in a modest fixed cost of $180, well within the range of estimates provided by Vissing-Jørgensen (2002). In the model, permanent income characteristics cause households to behave in a qualitatively different manner as costs are not proportional to income or asset purchases. Thus access and therefore the effect of an increase in income variance differs across groups. By analyzing the steady state responses to an increase in the transient part of income variance similar to that experienced by the US from 1980 to 2004, I show that the ESM model is consistent with the data for within-group variance of log consumption. This leads to the most important result of the paper: the observed increase in consumption inequality understates the true welfare effect of an increase in income variance as the consumption variance of high income households decreases while that of low income households increases. Thus any increase in aggregate consumption inequality is driven entirely by the low end of the income distribution.

An interesting avenue of future work is determining the effect of specific factors over which households can differ. An example of this is the positive correlation between education and savings behaviour, conditional on income, as documented in Lawrance (1991). More specifically, Lusardi and Mitchell (2007) examine the relationship between financial education or literacy on saving behaviour. The model can also be enriched by adding informational frictions in

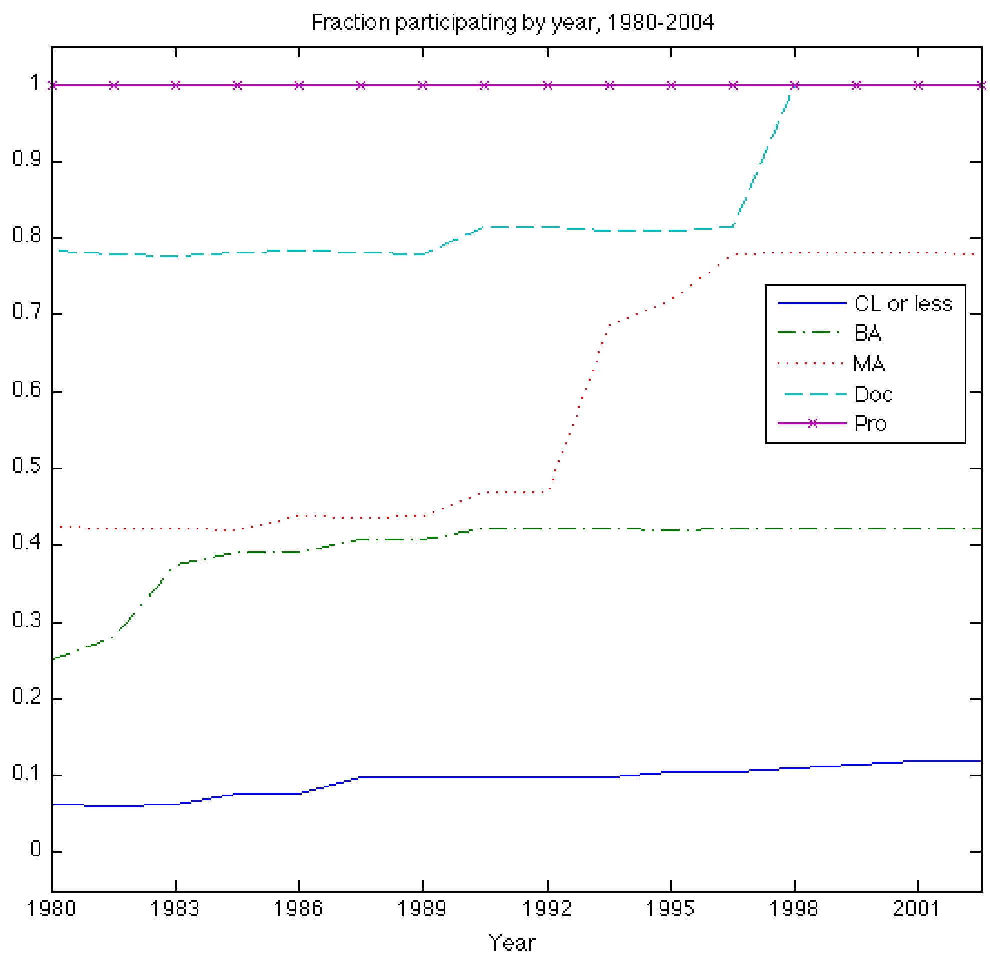

Figure 4.6: Fraction in complete markets, by year

the risk sharing agreement as in Athreya, Tam and Young (2008) who study the transfer of income risk to consumption variance in unsecured credit markets. As the age income profile of consumption variance has been measured over the same sample period (1980 to 1990 in each of the studies mentioned in this paper) measuring how this changes over time may inform the direction of future work, as any differences will indicate a change in some aspect of the household savings-consumption decision.

Chapter 5

Conclusion

This thesis has examined three topics relating to debt. In Chapter 2, I study the use of personal borrowing in the form of home equity loans by entrepreneurs to secure business financing during the Great Recession. In Chapter 3, I turned to the market for corporate bonds to study the disappearance of highly-rated corporate debt. Finally, in Chapter 4, I investigated the importance of costly access to financial markets for households of different incomes.

In Chapter 2, I make the striking observation that, despite house prices decreasing during the Great Recession, home equity loan balances increased, all while total debt did not change. The primary source of the increased use of home equity borrowing was entrepreneurs. I interpret this as evidence of binding financing constraints for entrepreneurs.

As entrepreneurs were not able to borrow during the credit crunch due to more stringent loan standards and less bank lending to small businesses, home equity loans allowed entrepreneurs to survive the crisis. Personal loans were a substitute for business loans. This confirms studies such as Quadrini (2000) that find that wealth is important for the entrepreneurship decision but deepens the understanding of how, exactly, wealth is used by entrepreneurs. In this case, housing wealth is used to ease credit constraints and to aid survival and entry. Of entrepreneurs in 2007, surviving entrepreneurs had higher rates of homeownership and higher house values relative to those that did not survive. Furthermore, continuing entrepreneurs increased borrowing against their home, while exiting entrepreneurs did not. Entrants in 2009 had more available housing wealth than those in 2007.

As discussed above, the drop in home equity resulted in 2007 entrepreneurs hiring fewer employees and an increased exit rate, which in turn resulted in job loss as well. Using the population weights provided with the SCF, changes in home equity, and the results obtained above we can derive a rough estimate of the change to employment. On average, the drop in home equity caused a drop of 0.23 employees per business for surviving entrepreneurs, roughly 5% of the observed drop per business (4.3). Furthermore, the drop in home equity caused roughly 28,000 entrepreneurs to exit, bringing with them 340,000 employees.

King & Levine (1993) show that effective financial systems that support entrepreneurship can have a significant impact on economic growth. This paper studies one channel that entrepreneurs might employ to finance their business when the usual financial channels are not available to them. Though entrepreneurs were able to use home equity loans to survive the Great Recession, it was not costless as more household wealth was exposed to business risk at the height of the recession. Considering the influence entrepreneurs have on growth and employment (see, for example, Adelino, Schoar & Severino, 2012) policies that ease borrowing constraints for entrepreneurs, such as the 7a loan program from the Small Business Administration, are a potentially beneficial means to improve aggregate conditions.

In Chapter 3, I document the disappearance of firms with high-credit ratings and analyze potential reasons for this change in the distribution credit ratings for firms. The change in the credit-rating distribution has been dramatic and has not been documented in the academic literature thus far. Possible explanations for this pattern, such as evolving credit rating agency standards, more highly levered firms, and firms merging, are explored and rejected.

Instead I propose a mechanism that captures the increase in the proliferation of firm information. Investors no longer rely solely on credit ratings to relay firm information and firms need no longer devote resources to unproductive ratings activities. Thus the demand for high ratings is lessened from both investors and firms, a story consistent with the changes purported by the financial press. However, due to regulations that require certain types of investors to hold only investment grade assets, credit ratings retain a certain value. Considering this, it is the value of the highest ratings relative to other investment grade ratings that has diminished.

The primary testable implication of the model is an increase in the dispersion of interest rates within a rating class. When the accuracy of the public signal is low, the interest rates given to two firms with the same rating and different signals will be closer than when the accuracy is high. In other words, public information does little to seperate borrowing costs across firms if it is not accurate. In effect, the difference between interest rates increases with the accuracy of public information as investors are more sure that these firms are of different underlying quality. I show that this pattern is borne out between 1990 and 2010.

Finally, in Chapter 4, I studied the effect of a fixed cost for market participation on consumption variance. In this chapter, I compared the qualitative and quantitative implications of a model with endogenously segmented markets (ESM) to a model representing each of the two standard classes in the macroeconomic literature. The first class are simple incomplete markets models in the spirit of Aiyagari (1994). These models over-predict the within-group log-consumption inequality and understate the between-group log-consumption inequality. The second class are models with limited commitment, such as in Kehoe and Levine (1993). The predicted within-group consumption inequality is lower than observed (counter to models with incomplete markets), while the between-group is higher (consistent with incomplete markets models.)

In the ESM model, permanent income characteristics cause households to behave in a qualitatively different manner as costs are not proportional to income or asset purchases. Thus access, and therefore the effect of an increase in income variance, differs across groups. This pattern is bourne out in the data, where poorer households participate is asset markets less frequently and to a smaller degree. To calibrate the model, I match the age profile of the variance of log consumption as first reported in Deaton and Paxson (1994). The calibration results in a modest fixed cost for market participation of \$180, well within the range of estimates provided by Vissing-Jørgensen (2002). By analyzing the steady state responses to an increase in the transient part of income variance similar to that experienced by the US from 1980 to 2004, I show that the ESM model is consistent with the data for within-group variance of log consumption. This leads to the most important result of the paper: the observed increase in consumption inequality understates the true welfare effect of an increase in income variance. This is because the consumption variance of high income households decreases, while that of low income households increases, and so any increase in aggregate consumption inequality is driven entirely by the low-end of the income distribution. In effect, income-poor households experience a larger increase in consumption variance than the economy as a whole.

An interesting avenue of future work is determining the effect of specific factors over which households can differ. An example of this is the positive correlation between education and savings behaviour, conditional on income, as documented in Lawrance (1991). More specifically, Lusardi and Mitchell (2007) examine the relationship between financial education or literacy on saving behaviour. The model can also be enriched by adding informational frictions in the risk sharing agreement as in Athreya, Tam and Young (2008) who study the transfer of income risk to consumption variance in unsecured credit markets. As the age income profile of consumption variance has been measured over the same sample period (1980 to 1990 in each of the studies mentioned in this paper) measuring how this changes over time may inform the direction of future work, as any differences (such as later retirement, more time spent in school, etc.) will indicate a change in some aspect of the household savings-consumption decision.

Appendix A

Supporting Tables (Chapter 2)

Table A.1: Percentage of Entrepreneurs in the U.S. Population, Various Definitions.

	Cross-section									Panel	
	1989	1992	1995	1998	2001	2004	2007	2010	2013	2007	2009
(1) Active Business Owner	11.6	13.4	11.6	11.7	12.3	12.4	12.5	12.4	10.8	12.7	13.2
(2) Business Owner	13.3	14.4	12.8	12.7	13.6	13.3	13.6	13.2	11.7	13.8	13.7
(3) Self-Employed	11.1	11.0	10.2	11.3	11.7	11.8	10.0	11.4	9.7	10.6	11.1
(4) Groups (1) and (3)	7.6	8.1	6.7	7.4	7.8	7.5	7.6	8.0	6.7	7.8	8.2
(5) New Entrepreneur	2.1	2.3	1.9	2.1	1.5	2.0	1.9	1.5	1.4	1.6	2.9

Note: "New Entrepreneur" is 2-or-less-year-old Active Business Owner.

Source: Survey of Consumer Finances.

Table A.2: Summary Statistics, All Households.

	All Households	
	2007	2009
Age	49	52
	48	50
Education (years)	13	13
	13	13
Nonfinancial Income	74,903	76,024
	46,000	49,000
Assets	669,616	582,674
	217,300	196,730
Debts	100,640	106,387
	33,580	35,000
House Value	207,072	182,730
	122,000	120,000
First Mortgage	68,357	69,237
	0	0
Home Equity Loans	6,145	6,837
	0	0
HELOC Limit	12,119	13,133
	0	0
Home Equity	132,570	106,656
	49,000	35,000
Homeownership	0.69	0.70
	1.00	1.00
N		3,857

Note: first row is the mean, second the median.
Source: Survey of Consumer Finances.

Table A.3: Summary Statistics, Workers and Entrepreneurs.

	2007		2009	
	Worker	Entrepreneur	Worker	Entrepreneur
Age	49	49	52	51
	48	49	50	50
Education (years)	13	14	13	15
	13	15	13	15
Nonfinancial Income	60,665	172,619	64,378	152,873
	40,000	83,000	43,500	90,000
Assets	434,147	2,285,690	381,758	1,908,507
	182,020	674,000	168,200	628,000
Debts	83,023	221,544	87,925	228,217
	24,300	140,000	25,400	133,000
House Value	177,225	411,915	154,821	366,899
	100,000	250,000	100,000	240,000
First Mortgage	58,075	138,929	59,407	134,107
	0	92,000	0	88,000
Home Equity Loans	4,587	16,836	4,637	21,349
	0	0	0	0
HELOC Limit	8,874	34,391	8,772	41,911
	0	0	0	0
Home Equity	114,564	256,151	90,777	211,442
	40,000	110,000	29,000	82,000
Homeownership	0.66	0.88	0.68	0.86
	1.00	1.00	1.00	1.00
N	2,712	1,145	2,725	1,132

Notes: (1) ‘Worker’ is any non-entrepreneur; (2) first row is the mean, second the median.
Source: Survey of Consumer Finances.

Table A.4: Description of variables used for probit regressions.

Variable Name	Description
Education	Education dummy variables. Relative to no high school
Risk Aversion	Answer to: "How much risk are you willing to accept on financial investments?" Relative to "no risk"
Years at Address	Years at current address
Years at Job	Years at current job
Delinquent	Missed payment by 60 days or more in the last year
Bankrupt	Indicator variable for whether the household was ever bankrupt
Net Worth	Value of total assets less value of debt, in percentiles, relative to first percentile
Own Home	Dummy variable for home ownership
Home Loan to Value	Ratio of all borrowing against the home to the value of the home
Home Equity	Home equity, in quintiles, relative to first quintile
New worth (percentile)	Total assets net of total debts, in percentiles
Liquid Assets	Total liquid assets, in quintiles, relative to first quintile
Other Assets	Total assets less house value, business value and liquid assets
Have Retirement Assets$*$Age	Interaction between indicator variable for having liquid retirement assets and age
Wage Income	Ratio of wage income to nonfinancial income
Retirement Income	Ratio of retirement income to nonfinancial income
Other Income	Ratio of other income to nonfinancial income
Credit Card Balance	Outstanding credit card debt
Debt Payments	Monthly debt payments
Housing Payments	Ratio of housing payments including rent to total payments
Consumer Debt Payments	Ratio of consumer debt payments to total payments
Debt Service Ratio	Ratio of total monthly debt payments to total monthly income
Business Value	Net business value
Employees	Number of employees at all actively-managed businesses
Personal Collateral	Value of personal collateral pledged for business loans
Service Industry	Indicator variable for whether business is in the service industry, defined as retail, finances, services or public.

Table A.5: Summary statistics, 2007 Entrepreneurs.

	2007		2009	
	Exit	Continue	Exit	Continue
Non-financial Income	112,067	187,230	100,485	162,690
	73,000	85,200	66,900	90,000
Assets	1,240,945	2,537,786	856,009	2,169,678
	479,000	771,900	321,200	693,400
Debts	174,283	232,948	147,748	243,886
	112,000	145,000	76,540	142,000
House Value	289,611	441,427	249,822	389,452
	185,000	275,000	175,000	250,000
First Mortgage	110,190	145,863	92,095	141,848
	72,000	96,000	30,000	95,000
Home Equity Loans	9,014	18,723	8,732	23,179
	0	0	0	0
HELOC Limit	16,745	38,648	14,516	43,807
	0	0	0	0
Home Equity	170,408	276,840	148,996	224,424
	73,000	121,000	48,000	90,000
Homeownership	0.83	0.89	0.79	0.89
	1.00	1.00	1.00	1.00
Home Loan-to-value	0.52	0.64	0.47	0.70
	0.54	0.44	0.50	0.51
N	146	999	146	999

Note: first row is the mean, second the median.

Source: Survey of Consumer Finances.

Table A.6: Summary statistics, 2007 entrepreneurs who are also homeowners.

	2007		2009	
	Exit	Continue	Exit	Continue
Non-financial Income	124,036	198,711	114,918	172,211
	86,000	90,000	80,000	94,000
Assets	1,459,693	2,732,855	1,076,663	2,357,695
	500,800	841,900	390,640	746,000
Debts	200,503	254,660	177,390	269,474
	149,000	164,400	117,000	170,300
House Value	350,224	494,140	317,663	436,054
	241,000	310,000	205,000	284,000
First Mortgage	133,251	163,282	117,104	158,822
	92,000	110,000	89,000	112,000
Home Equity Loans	10,900	20,959	11,103	25,952
	0	0	0	0
HELOC Limit	20,250	43,264	18,458	49,049
	0	0	0	0
Home Equity	206,072	309,899	189,457	251,279
	100,000	145,000	90,000	117,000
Home Loan-to-value	0.52	0.64	0.47	0.70
	0.54	0.44	0.50	0.51
N	133	942	130	948

Note: first row is the mean, second the median.

Source: Survey of Consumer Finances.

Appendix B

Supporting Material (Chapter 3)

B.1 Confidence Intervals on the Coefficient of Variation

Suppose random variable X is distributed log-normal with mean μ and standard deviation σ. We would like to construct a confidence interval on the coefficient of variation, $CV = \sqrt{Var(X)}/E(X)$. Helpfully, the coefficient of variation for a random variable distributed log-normal does not depend on the mean and can be entirely characterized by the variance.

Begin by determining the theoretical or "true" test statistic. The following are properties of log-normal distributions:

$$E(X) = \exp(\mu + \frac{1}{2}\sigma^2) \tag{B.1}$$

$$Var(X) = \exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1) \tag{B.2}$$

$$CV = \sqrt{\exp(\sigma^2) - 1}. \tag{B.3}$$

Now, let $Y = \ln X$. Random variable Y is distributed $N(\mu, \sigma^2)$ and the test statistic for σ^2 is:

$$\frac{(n-1)s^2}{\sigma^2} \sim \chi^2_{n-1}.$$

The lower and and upper bounds can be defined as follows:

$$a_L \equiv \frac{(n-1)s^2}{F_{\chi^2}(n-1)^{-1}(1-\alpha/2)}$$

$$a_U \equiv \frac{(n-1)s^2}{F_{\chi^2}(n-1)^{-1}(\alpha/2)}$$

Where $F_{\chi^2}(n-1)^{-1}(1-\alpha/2)$ is the cumulative distribution function for a chi-squared distribution with $n-1$ degrees of freedom.

Using these bounds on σ^2 and equation (B.3), the following is a $1-\alpha$ confidence interval for the coefficient of variation of X:

$$\left[\sqrt{\exp(a_L)-1},\ \sqrt{\exp(a_U)-1}\right]. \tag{B.4}$$

In order to compute the $(1-\alpha)\%$ confidence interval of the coefficient of variation, all that is needed is the sample size, n, and the sample variance, s^2.

B.2 Support for Proposition (3.4.1)

It is required to show that the probability that a firm is of good type given credit rating A or C and any public signal is decreasing in a firm's rating investment, i. That is,

$$\frac{\partial \Pr(g|\kappa,\nu)}{\partial i} < 0 \quad \forall \nu, \kappa = A, C$$

where

$$\begin{aligned}\Pr(g|\kappa,\nu) &= \frac{\Pr(\kappa|g,\nu)\Pr(\nu|g)\Pr(g)}{\Pr(\kappa|g,\nu)\Pr(\nu|g)\Pr(g)+\Pr(\kappa|b,\nu)\Pr(\nu|b)\Pr(b)}\\ &= \frac{\pi_\kappa(g,i_\nu)\Pr(\nu|g)\lambda}{\pi_\kappa(g,i_\nu)\Pr(\nu|g)\lambda+\pi_\kappa(b,i_\nu)\Pr(\nu|b)(1-\lambda)} \end{aligned}\tag{B.5}$$

and, collecting like terms,

$$\frac{\partial \Pr(g|\kappa,\nu)}{\partial i} = \frac{(\pi_\kappa^{'}(g)\pi_\kappa(b,i_\nu)-\pi_\kappa^{'}(b)\pi_\kappa(g,i_\nu))\Pr(\nu|g)\Pr(\nu|b)\lambda(1-\lambda)}{(\pi_\kappa(g,i_\nu)\Pr(\nu|g)\lambda+\pi_\kappa(b,i_\nu)\Pr(\nu|b)(1-\lambda))^2} \tag{B.6}$$

$$= \Phi\frac{\Pr(\nu|g)\Pr(\nu|b)\lambda(1-\lambda)}{(\pi_\kappa(g,i_\nu)\Pr(\nu|g)\lambda+\pi_\kappa(b,i_\nu)\Pr(\nu|b)(1-\lambda))^2}. \tag{B.7}$$

To determine the sign of equation (B.7) we must determine only the sign of Φ, where

$$\Phi = \pi_\kappa^{'}(g)\pi_\kappa(b,i_\nu)-\pi_\kappa^{'}(b)\pi_\kappa(g,i_\nu)$$

as all other terms and factors are positive by definition or nature. It will become evident that the results are symmetric for each value of ν as investment, i, which may depend on ν, does not enter the key term. As such, there are two cases to check: a good-type firm which receives a credit rating of A or C. Recall that $\sigma_1^\theta+\sigma_2^\theta+\sigma_3^\theta = 1$ for $\theta = g, b$ and $\sigma_1^\theta > 0$ for $\theta = g, b$ under Assumptions (3.1) and (3.2).

Case 1: $\kappa = A$

$$\begin{aligned}\Phi &= (\sigma_2^g + \sigma_3^g)(\sigma_2^b + \sigma_2^b)i_\nu - (\sigma_2^b + \sigma_2^b)(\sigma_1^g + (\sigma_2^g + \sigma_2^g)i_\nu) \\ &= -(\sigma_2^b + \sigma_2^b)\sigma_1^g \\ &< 0\end{aligned}$$

Case 2: $\kappa = C$

$$\begin{aligned}\Phi &= -\sigma_g^3(\sigma_1^b + \sigma_3^b(1 - i_\nu)) - (-\sigma_3^b)\sigma_3^g(1 - i_\nu) \\ &= -\sigma_3^g\sigma_1^b \\ &< 0\end{aligned}$$

This result implies

$$\frac{\pi'_\kappa(g)}{\pi_\kappa(g,i)} < \frac{\pi'_\kappa(b)}{\pi_\kappa(b,i)}$$

for ratings A and C. This has implications which are discussed in Proposition (3.4.1).

Proof of Proposition 3.4.3

Proposition 3.4.3 is repeated here for the reader's benefit.

Proposition B.2.1 *Consider ω_1, ω_2. Let $R^j(A,\nu)$ be the equilibrium interest rate for firms rated A with signal ν when $\omega = \omega_j$. Then, for any ω_1, ω_2 such that $\omega_1 < \omega_2$,*

$$R^1(A,L) - R^1(A,H) < R^2(A,L) - R^2(A,H).$$

Proof I first derive the derivative of the equilibrium interest rate $R^*(A,H)$ with respect to ω and show that $R^*(A,H)$ decreasing in ω as this derivative is negative. Second, I derive the derivative of the equilibrium interest rate $R^*(A,L)$ with respect to ω and show that $R^*(A,L)$ increasing in ω as this derivative is positive. Recall,

$$R^*(\kappa,\nu) = r\frac{\Pr(\nu|g)\lambda\pi_\kappa(g,i_\nu^*)\gamma_g + \Pr(\nu|b)(1-\lambda)\pi_\kappa(b,i_\nu^*)\gamma_b}{\Pr(\nu|g)\lambda\pi_\kappa(g,i_\nu^*) + \Pr(\nu|b)(1-\lambda)\pi_\kappa(b,i_\nu^*)}.$$

Taking the first derivative of $R^*(A,H)$ and $R^*(A,L)$ with respect to ω and collecting like terms:

$$\begin{aligned}\frac{\partial R^*(A,H)}{\partial\omega} =& r\lambda(1-\lambda)(\gamma_G - \gamma_B)\frac{\partial i_H^*}{\partial\omega} \\ &\times \frac{\left(\omega\pi_A(g,i_H^*)\frac{\partial\pi_A(b,i_H^*)}{\partial i_H^*} + (1-\omega)\pi_A(b,i_H^*)\frac{\partial\pi_A(g,i_H^*)}{\partial i_H^*}\right)}{\left(\omega\lambda\pi_A(g,i_H^*) + (1-\omega)(1-\lambda)\pi_A(b,i_H^*)\right)^2}\end{aligned}$$

$$\begin{aligned}\frac{\partial R^*(A,L)}{\partial \omega} =& -r\lambda(1-\lambda)(\gamma_G-\gamma_B)\frac{\partial i_L^*}{\partial \omega}\\ &\times \frac{\left(\omega\pi_A(g,i_L^*)\frac{\partial \pi_A(b,i_L^*)}{\partial i_L^*}+(1-\omega)\pi_A(b,i_L^*)\frac{\partial \pi_A(g,i_L^*)}{\partial i_L^*}\right)}{\left(\omega\lambda\pi_A(g,i_L^*)+(1-\omega)(1-\lambda)\pi_A(b,i_L^*)\right)^2}.\end{aligned}$$

By Proposition 3.4.1, $\frac{\partial i_\nu^*}{\partial \omega} < 0$ for $\nu = H, L$. By assumption, $\frac{\partial \pi_A(\theta,i_\nu^*)}{\partial i_\nu^*} > 0$ for $\theta = g, b; \nu = H, L$ and $(\gamma_g - \gamma_b) > 0$. Therefore $\frac{\partial R^*(A,H)}{\partial \omega}$is negative and $\frac{\partial R^*(A,L)}{\partial \omega}$ is positive. Finally, as $R^*(A,H)$ is decreasing in ω and $R^*(A,L)$ is increasing in ω, $R^*(A,L) - R^*(A,H)$ is increasing in ω.

Appendix C

Supporting Figures (Chapter 4)

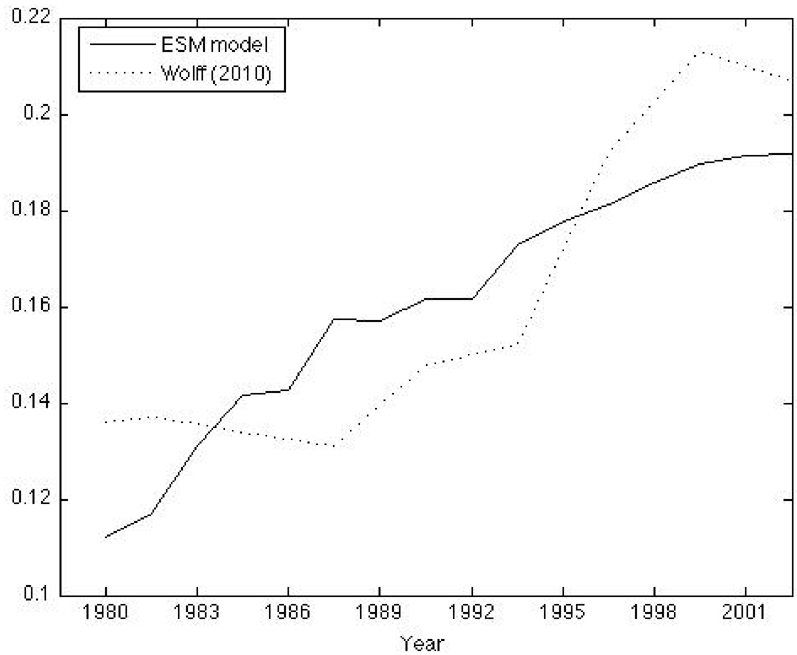

Figure C.1: Simulated participation in complete markets and measured participation in financial markets, percentage of population, 1980-2004

Source: Survey of Consumer Finances via Wolff (2010).

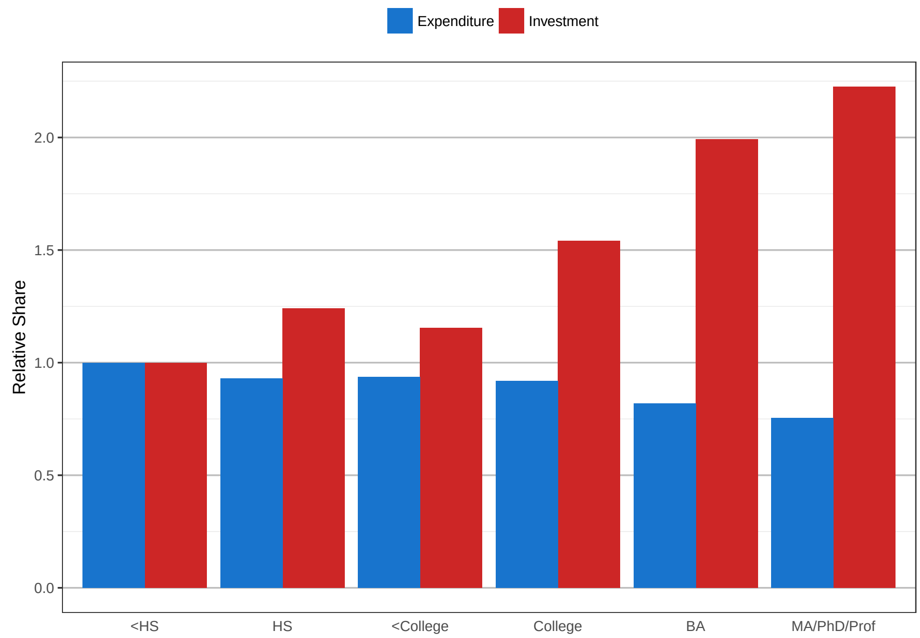

Figure C.2: The relative share of income devoted to expenditure and the relative share coming from investment, by educational attainment.

Note: Each share relative to “No High School” share. Source: Consumer Expenditure Survey.

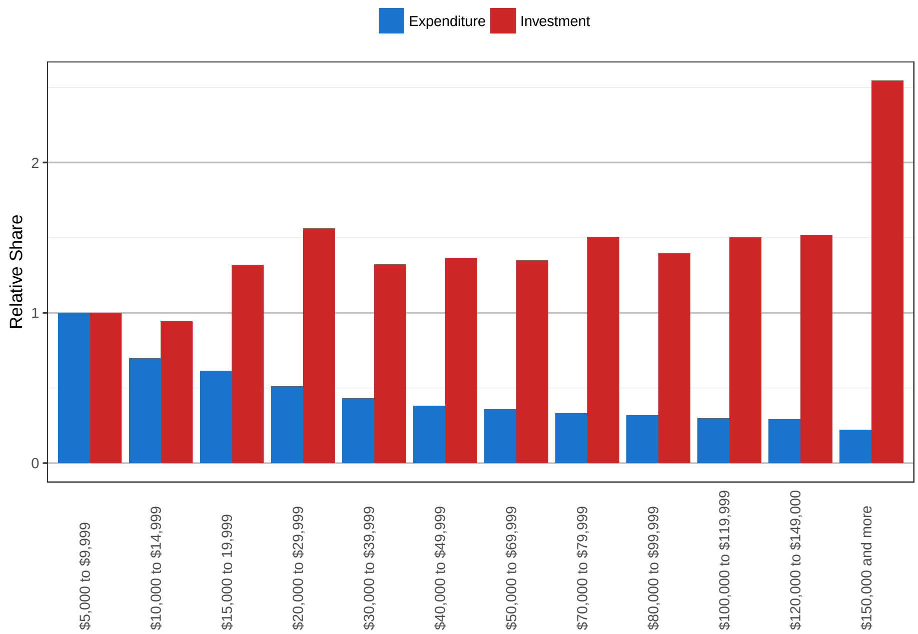

Figure C.3: The relative share of income devoted to expenditure and the relative share coming from investment, by income group.

Note: Each share relative to lowest income share. Source: Consumer Expenditure Survey.

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