Moral Hazard and Adverse Selection for Subprime Lending and Securitization – Priced or not Priced?

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March 2009

Abstract

This paper provides an overall test of whether prices in the subprime mortgage market reflect the quality of the underlying loans. One hypothesis is that the subprime mortgage market is a lemons market in which investors may end up with poor quality securities and pay prices unrelated to quality. The paper's method of testing this hypothesis is to use high loan denial rates to identify subprime lenders with good underwriting practices, and use low loan denial rates to identify lenders with less stringent underwriting practices. The paper then matches this data to a dataset containing the initial yields on subprime ABSs issued over the period 2004-2007 and to the CDS spreads of home equity issuers over this same time period. The initial ABS yields provide us with investors' assessment of the credit risk associated with the ABS notes. The CDS spreads of the home equity issuers provide us with investors' assessment of the credit risk associated with their loan portfolios – the value of which will typically include first-loss pieces. We then use these spreads to test whether there is tiering between issuers and find positive results. This leads to a rejection of the hypothesis that bad loans have driven out good loans in the subprime market.

Keywords: Mortgages, Asymmetric and Private Information, and Asset Pricing.

JEL Classification: G2, D82, and G12.

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1. Introduction

This paper analyses whether there is a lemons market in the subprime mortgage market with respect to loan quality. There are good loans and bad loans in the subprime mortgage market and good lenders versus bad lenders, but because of asymmetric information, and because of so-called liar loans – mortgages approved without requiring proof of the borrower's income or assets – and ninja loans – short for no income, no job, and (no) assets loans, for which all sorts of information asymmetries existed between the borrower and primary lender, it is not clear whether loan quality is distinguishable beforehand in the subprime mortgage market. Given this informational asymmetry, one could argue that a lemons market existed, in which an investor's best guess for a given subprime mortgage was that the loan was of average quality. Accordingly, this means that wary secondary market investors should have been unwilling to pay high prices for subprime loans as they expected low-quality mortgages (lemons). Therefore, primary lenders would have been unwilling to sell their high-quality subprime loans in secondary market, causing quality to deteriorate to such a level that the market would cease to exist, as in Akerlof (1970).

We find this description of the subprime mortgage market interesting because it can explain much of the subprime mess. Yet, on the other hand, the self-selection against the secondary market is something that the subprime market should have been able to gaurd against. Pavel (1986), Greenbaum and Thakor (1987), and Pavel and Phillis (1987) worked out the theory in the 1980s. The theory is fittingly simple. By working in a local market, primary lenders know much more about that local market and about the mortgage borrower than do secondary market investors. Presumably, secondary market investors realize this, and so they require primary lenders to keep a substantial first-loss piece on their balance sheet, so that they know these loans are underwritten assuming that they would be held to maturity. In addition, secondary market investors require as assessment of creditworthiness from a credit rating organization, so that buyers and sellers share the same information. In this case, different quality of subprime loans should be priced differently by the market.

In this paper we use this distinction to test whether the subprime mortgage market was a lemons market with respect to loan quality. Essentially, if the lemons outcome existed, loan quality distinctions would not be observed by investors prior to loan purchase. Alternatively, if a loan's quality were observable beforehand by investors, tiered pricing should have existed, whereby different subprime lenders were paid different prices for the loans they originated and sold.

Of course, credit rating organizations may have had an idea of the loan's quality from historical loan performance experience, and they may have adjusted the security's subordination level accordingly. However, it is not clear that credit ratings were accurate or that credit rating organizations had the proper incentives to assess creditworthiness and credit quality (see, e.g., Caprio, Demirgüç-Kunt, and Kane (2008)).

To test the hypothesis that the market priced riskier subprime asset-backed securities (ABSs) differently to compestate for the risks they created, we look cross-sectionally (and over time) at the pricing of these securities, and ask whether there is tiering between issuers – i.e., whether subprime originators who sell lower quality loans are charged different prices than subprime lenders who originate and sell higher quality loans. Such pricing would tells us that all was not doomed to fail from the start.

To determine whether loans sold are of high or low quality, we shall follow the general approach of Schafer and Ladd (1981), Ladd (1982), Goering and Wienk (1996), Munnell et al.

(1996), Ling and Wachter (1998), Avery et al. (1999), Lin (2001), and Apgar, Bendimerad, and Essene (2007) in fitting a loan denial model to mortgage applications data. In this work, the loan denial rate is a function of variables that affect the risk of default, those that affect the costs of default, loan characteristics, and personal characteristics of the borrower. Among the latter include 0-1 dummy variables to test for the practice of banks and other lending institutions denying loans to one or more groups of borrowers primarily on the basis of race, ethnic origin, or sex.

Our interest in these models is in comparing normal loan denial rates across subprime lenders. We do this by including fixed effects for individual lenders. These lender fixed effects (which are allowed to vary over time) are most consistent under a wide range of circumstances; they measure the extent to which individual subprime lenders are underwriting high-quality loans, all else equal.

The proxy used to measure the price of the first-loss piece in this analysis is the lender's credit default swap (CDS) spread. As shown by Duffie (1998), Duffie and Singleton (1997, 1999), and Lando (1998), CDS spreads are pure measures of default risk. As such, the spreads should reflect the composition of the lender's loan portfolio and its default risk; and hence it should vary inversely with the lender's loan denial rate.

Our approach to testing how subprime ABSs are priced differs from that of Franke and Krahnen (2005). The Franke and Krahnen study is specifically concerned with the default risk sharing between banks and the market; their findings suggest that only a small portion of default losses of the underlying portfolio is transferred in a CDO-transaction. They look at all transactions in Moodys European Securitization list of June 2003; this includes 254 CDO-transactions, of which 185 have a Moodys New Issue Report. Adams, Einav, and Levin

(2007) examine the informational problems facing a large auto sales company that originates loans to subprime customers with low incomes and poor credit histories. Adams, Einav, and Levin track loan repayment histories; they find that modern credit scoring can go a significant distance toward mitigating adverse selection problems. Gorton and Souleles (2005) examine credit-card ABSs issued between 1988 and 1999; they find that the risk of the sponsoring firm, because of implicit recourse, affects the risk of the ABS that are issued by its special purpose vehicles. We in this paper analyze subprime ABS spreads and CDS spreads of home equity issuers over the period 2004-2007. The subprime ABS spreads allow us to test the Gorton-Souleles hypothesis in the case of the subprime mortgage market.

The remainder of the paper is organized as follows. In section 2, we provide a description of the subprime mortgage market. Section 3 continues with a description of who is a subprime borrower. In Section 4, we estimate a logit model of the probability of loan denial (with lender fixed effects). Section 5 tests the tiering hypothesis. Section 6 concludes.

2. Description of the Subprime Mortgage Market

Clearly having an understanding as to how subprime mortgages are funded is the first step in testing the existence of tiered pricing. Most subprime mortgages were packaged into ABSs and sold to investors in the secondary market. In this security design, repayment risk was sliced into tranches, with the lowest priority tranche bearing any initial losses. Any additional losses in excess of the lowest priority tranche was absorbed by the subsequent tranche and so on, leaving the highest priority tranche only with a remote probability of loss. Here we simplify the discussion by considering just two classes of bonds senior and subordinated that are supported by the underlying mortgages. There is no loss of generality for the analysis by limiting the number of bond classes to two. The subordinated bonds are the junk pieces that absorb the first fraction of any losses up to the limit of their nominal values, and only then are further losses absorbed by the senior bonds. We also have a first-loss piece or equity piece that is held by the originator. The first-loss piece receives all principal and interest paid on the underlying securities in excess of the amount of principal and interest required to be paid to the other bond classes.

We illustrate the aggregate demand and supply curves for this ABS security in Figure 1. The horizontal axis measures the debt ratio (total loanable funds divided by assets). The vertical axis measures the nominal interest rate. The schedule D_{AAA} represents the market's demand for senior ABS bonds backed by subprime mortgages. The D_{AAA} schedule expresses the demand for senior ABS bonds as an increasing function of the interest rate.

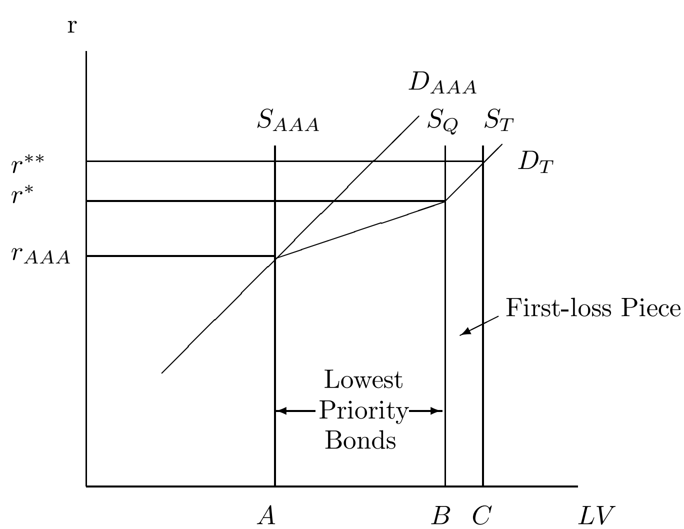

Figure 1: The Demand for and Supply of Subprime ABS Bonds. Vertical axis: Nominal interest rate. Horizontal axis: Debt ratio (i.e., total loanable funds divided by assets). D_{AAA} = Demand for senior ABS bonds. D_T = Sum of the

aggregate demands for senior and subordinated ABS bonds. S_{AAA} = Fixed supply of senior ABS bonds. S_Q = Fixed supply of ABS bonds. S_T = Fixed supply of subprime mortgages. r_{AAA} = Interest rate on senior ABS bonds. r^{**} = Interest on subordinated ABS bonds. r^{***} = Interest rate on first-loss piece.

The schedule D_T is the sum of the aggregate demands for senior and subordinated ABS bonds plus the demand for the first-loss piece. This schedule is drawn for given values of a large set of exogenous variables, including the expected drift and variability of future house prices.

We designate three supply curves, S_{AAA}, S_Q, and S_T. The supply curve S_{AAA} is the aggregate supply of senior ABS bonds in the economy. This supply curve applies to D_{AAA}. This curve is vertical because a debt-to-asset ratio of A implies a relatively low probability of default.

The supply curves S_Q and S_T are also fixed. The supply curve S_Q is equal to the total quantity of ABS bonds in the economy. The positions of both S_{AAA} and S_Q are determined by the credit rating organizations based not on prices but default probabilities (which is the only relevant matter to a credit rating organization). The supply curve S_T is assumed to be equal to the total quantity of subprime mortgage funds in the economy.[1] The position of this supply curve is therefore determined primarily by the demand for housing services.

The horizontal difference between S_Q and S_{AAA} is the supply of subordinated ABS bonds. Similarly, the horizontal difference between S_T and S_Q is the supply of subprime equity. If we assume A is determined correctly by credit rating organizations, then the riskiest part of any mortgage is the portion of the loan exceeding A. This portion of the loan (including the

[1] This assumption is a limiting case. It implies that all subprime mortgages are packaged into ABSs and sold to investors in the secondary market. In reality, of course, some subprime mortgages are, in fact, originated and held by a number of lending institutions. However, this latter outcome is rare (especially for the major subprime lenders). Hence, we have decided to ignore this possibility for the sake of (some) simplicity.

equity tranche) therefore serves to protect the security interest of the senior priority tranche.

In the equilibrium shown in Figure 1, the interest rate on the senior ABS bonds, r_{AAA}, is uniquely determined by D_{AAA}. Clearly, this interest rate should be approximately equal to the AAA-corporate bond rate; otherwise, an arbitrage opportunity would exist, and the position of D_{AAA} would adjust to arbitrage the under- or over-pricing away.

Figure 1 also shows the interest rate on the first-loss piece. This interest rate is r^{**}, and the quantity of total loanable funds supplied is equal to C. For our purposes here, once A and C are determined, it is up to the credit rating organization to determine the size of the equity tranche $C - B$, which will absorb all losses first due to default and foreclosure until its principal is exhausted, and the size of the subordinated ABS bonds $B - A$.

2.1 The Effect of Re-Packaging

In theory, the cost of an ABS can be lowered by issuing a cash-flow CDO in which the reference assets are themselves the lowest priority tranches of an ABS. Figure 2 illustrates why, in our simple example of just two classes of bonds, this is true.

In Figure 2, D_T depicts the aggregate demand curve for subprime mortgages before the issuing of a cash-flow CDO. D_{AAA} is a demand curve for senior ABS bonds that remains unchanged, and $D_T - D_{AAA}$ is the initial demand by subordinated bondholders and ABS issuer whose demand will later increase to $D_T^{'} - D_{AAA}$ (owing to an increase in the number of investors bidding on the subordinated ABS bonds). Here we assume that the cost of adverse selection remains constant. In section 2.4 below, we allow adverse selection to vary.

S_T is the aggregate supply of subprime mortgages, which remains fixed. Initially, the interest rate on the highest priority tranche is r_{AAA}, with A amount of senior bonds being sold, and the interest rate on the underlying mortgages is r^*, with the quantity of total loanable funds supplied equal to C.

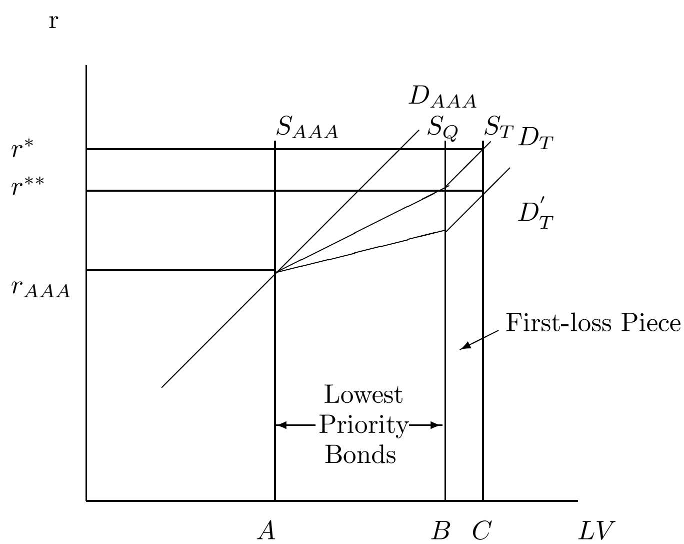

Figure 2: The Effect of Re-Packaging on the Demand for and Supply of Subprime ABS Bonds. Vertical axis: Nominal interest rate. Horizontal axis: Debt ratio (i.e., total loanable funds divided by assets). D_{AAA} = Demand for senior ABS bonds. D_T = Sum of the aggregate demands for senior and subordinated ABS bonds. D_T' = Aggregate demand for senior and subordinated ABS bonds after the re-packaging of the security. S_{AAA} = Fixed supply of senior ABS bonds. S_Q = Fixed supply of ABS bonds. S_T = Fixed supply of subprime mortgages. r_{AAA} = Interest rate on senior ABS bonds. r^* = Shadow interest rate on first-loss piece on subprime mortgages. r^{**} = Interest rate on first-loss piece.

By re-packaging the first-loss piece of this security into a cash-flow CDO, the originator can divide the securities into tranches (where some tranches now should be less prone to bankruptcy risk, owing to the additional geographic diversification), and then re-sell these tranches at different marginal prices.[2] Presumably the buyers of these tranches are willing

[2] Pooling risk in this case does not change the default risk for any particular mortgage, but it does reduce the overall risk. To pool the risk, the originator would have to include lots of mortgages in different geographic locations, locations that will (hopefully) not experience an increase in default risk all at the same time. But this is what a cash-flow CDO is intended to do.

to invest because the price may be just slightly under their marginal personal values (or equivalently, the promised interest rate may be just barely over their required rate of return).

With respect to the ABS originator, he or she is able to profit from the issuance of the CDO for one of two reasons. Either he or she is able to profit from the additional geographic diversification (i.e., selling some securities with less bankruptcy risk), or he or she is able (knowing the buyers' personal-valuation schedules in Figure 2) to capture a larger portion of the gain from trade by re-selling these securities at a series of different prices.

Figure 2 shows the impact on the demand for subprime mortgages. The entrance of new subordinated bond buyers (those interested in re-packaging the security) increases the demand for subordinated bonds, thus causing D_T to shift to the right enough to match the increase in the demand for the subordinated bonds. The final equilibrium is thus achieved at some interest rate below, r^*, say r^{**}, as subordinated bond buyers bid up the price of the subordinated bonds and bid the interest rate on subprime mortgages. The total supply of subprime mortgages remains at C, due to the fact that we have assumed that the demand for housing services by subprime borrowers remains fixed (below we shall relax this assumption).

Consider next the case of issuing a CDO-squared, which is a synthetic CDO in which the reference assets are themselves the lower priority tranches of a CDO. By re-packaging these securities into a synthetic CDO, the originator can further divide the securities into tranches (where some tranches should again be less prone to bankruptcy risk, owing to the additional geographic diversification). Again, this re-packaging allows the originator to expand the market for the lowest priority ABS tranches, thereby causing D_T in Figure 2 to shift further to the right.

2.3 Regulatory Arbitrage

ABS issuers may have any of several motivations. ABSs may be issued to raise leverage. The ABS issuer may set up a hedge fund, with the objective of trading in the highest risk (i.e., lowest priority) tranches. Next, the hedge fund may leverage the portfolio in order to achieve even higher returns.

ABSs may also be issued to manage risk. Subprime lenders may rely on ABSs to dispose of risky loans when they see opportunities (i.e., try to parcel out bad quality loans), or they may issue ABSs to match investor preferences for risk better.

ABSs may also be used for regulatory arbitrage purposes, with a view of taking advantage of the difference (if any) between regulatory and market-based capital requirements. Subprime lenders who hold their loans on their balance sheets typically set their prices on the basis of regulated-based capital requirements. In contrast, subprime lenders who mostly rely on ABSs to dispose of loans typically set their prices on the basis of market-based capital requirements. When the latter are less stringent than the former, the demand curve for subprime ABSs D_T will lie to the right of the demand curve for whole loans D_M (i.e., subprime ABS issuers will have a marginal cost advantage viz. regulated banks).

The impact of this regulatory arbitrage is to reduce the equilibrium interest rate and increase the extent of beneficial trade. Figure 3 is a graphic illustration of this. As r is reduced through regulatory arbitrage, this shifts the aggregate supply curve S_T to the right, allowing subprime lenders to serve a larger, and riskier part (i.e., higher debt-to-asset ratio) of the subprime market, and encouraging subprime borrowers to invest more.

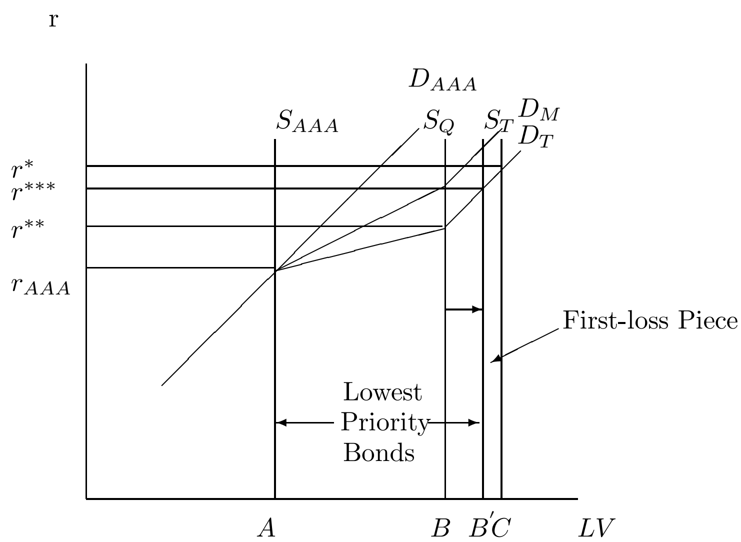

Figure 3: The Effect of Regulatory Arbitrage on the Subprime Mortgage Market. Vertical axis: Nominal interest rate. Horizontal axis: Debt ratio (i.e., total loanable funds divided by assets). D_{AAA} = Demand for senior ABS bonds. D_T = Sum of the aggregate demands for senior and subordinated ABS bonds. D_M = Aggregate demand for whole subprime loans. S_{AAA} = Fixed supply of senior ABS bonds. S_Q = Fixed supply of ABS bonds. S_T = Fixed supply of subprime mortgages. $S_T^{'}$ = Increased supply of ABS bonds. r_{AAA} = Interest rate on senior ABS bonds. r^* = Interest rate on first-loss piece on subprime mortgages. r^{**} = Interest rate on subordinated ABS bonds. r^{***} = Interest rate on subordinated ABS bonds after increase in supply.

At the same time, because D_T is upward-sloping, the shift in the aggregate supply curve (as shown by increasing from S_T to $S_T^{'}$) increases the interest rate on subordinated ABS bonds from r^{**} to r^{***}.

Figure 3 is quite consistent with the rapid growth in subprime mortgages that are now outstanding, and with almost every subprime loan being securitized the lender. Figure 3 is also consistent with the rapid rise in subprime mortgage specialists, mortgage brokers, and mortgage bankers over time. Much of what is unique about the rapid rise in these subprime mortgage specialists is that pure lending on the company's own books is very rare; instead, these lenders mostly sell their mortgages to secondary market investors (or rely on whole-loan sales to dispose of their loans).

Of course, an argument can be made (especially now in hindsight) that the aggregate demand D_T was where it was at over the last several years (i.e., to the right of D_M) not because of regulatory arbitrage, but due to risk misperception. Obviously, risk misperceptions could have (temporarily) led ABS investors to underprice the credit risk involved in subprime mortgages (seeing that it is not clear that anyone has an especially good empirical subprime default model). Consequently, in the interim, a really risky security could have been overvalued.

2.4 The Moral Hazard and Adverse Selection Problem

We are now interested in how moral hazard and adverse selection affects the pricing of subprime ABSs. We begin our examination of this issue by assuming asymmetric information is present, but not substantial. As the value of the residual claim decreases, moral hazard increases (i.e., subprime lenders are now motivated to originate and sell risky loans into the secondary market in order to collect fees). As a result, a lemons market may develop in which the demand for subprime ABSs should shift from D_T to $D_T^{'}$, as illustrated in Figure 4. Note that $D_T^{'}$ is to the left of D_T because ABS investors are now very reluctant to pay a high price for the lowest priority tranches, not knowing the odds that the loan will default. Accordingly, the subprime mortgage rate should increase.

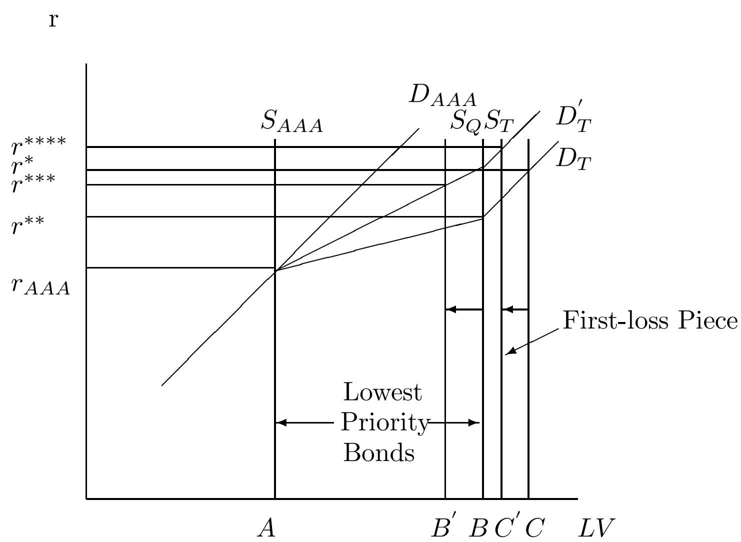

Figure 4: The Effect of Moral Hazard and Adverse Selection on the Subprime ABS Market. Vertical axis: Nominal interest rate. Horizontal axis: Debt ratio (i.e., total loanable funds divided by assets). D_{AAA} = Demand for senior ABS bonds. D_T = Sum of the aggregate demands for senior and subordinated ABS bonds. D_T' = Decreased aggregate demand for subprime ABS bonds. S_{AAA} = Fixed supply of senior ABS bonds. S_Q = Fixed supply of ABS bonds. S_T = Fixed supply of subprime mortgages. S_T' = Increased supply of ABS bonds. r_{AAA} = Interest rate on senior ABS bonds. r^* = Interest rate on first-loss piece on subprime mortgages. r^{**} = Interest rate on subordinated ABS bonds. r^{***} = Interest rate on subordinated ABS bonds after increase in supply. r^{***} = Interest rate on first loss piece after increase in supply.

Next, as the subprime mortgage rate increases, we would expect some subprime borrowers to be reluctant to borrow in the subprime market, causing the supply curve for subprime mortgages to shift from S_T to S_T', as illustrated in Figure 4. But, of course, we would not expect much of a decrease in S_T, since, after all, this is the subprime market, and most subprime borrowers have no other option but to apply for a subprime loan.

The market equilibrium in Figure 4 occurs at a much lower demand and reduced supply. In this equilibrium, ABS investors are (or should be) pricing all subprime mortgage loans at a higher interest rate. With some, but not substantial, asymmetric information, we would expect tiered pricing to result, in which subprime originators selling lower quality loans are charged different prices than subprime lenders selling higher quality loans. Alternatively, with substantial asymmetric information, we would expect ABS investors to lower the price for all ABS securities. In this case, without the necessary information on the value/quality of the underlying loans, the low quality ABS securities would begin to drive out the high quality ABSs, which results in a market of lemons and potential market failure – and yes in this case the subprime ABS market would pretty much be doomed from the start (so perhaps we should not be surprised that the subprime ABS market has failed).

These theoretical implications lead to the following testable hypothesis. With all sorts of asymmetric information in the subprime mortgage market (liar loans, ninja loans, option ARMs, etc.), the market may not have had enough information to price high- and low-quality loans differently. Such a finding would be consistent with the observation that the subprime ABS market was doomed from the start. Of course, short of that finding, we would expect learning to occur over time (with a lag) and a teiring between issuers to ensue, where the better quality issuers are charged lower ABS spreads than low quality issuers. We propose to test this hypothesis directly by examining whether the risk pricing of the subordinated ABS bonds reflects the risk profile of the underlying mortgages (as measured by loan denial rates). Further, holding all else equal, ABS issuers who have low denial rates should also have high CDS rates on the first-loss pieces held on their balance sheets. Needless to say, it may take time for investors to learn about the practices of the subprime lenders. Under this learning conjecture, learning should gradually (with a lag) lead to higher ABS spreads on lower quality loans. Of course, whether this learning takes place at all is debatable. Further, if credit rating organizations had an idea of the loan's quality from historical loan performance experience, they may have adjusted the security's subordination level accordingly, thereby offsetting the increased riskiness of the underlying loans. However, it is unclear whether credit rating organizations did not allow securitization of a mixed bags of loans, and then rated them at AAA in order to collect fee income (Caprio, Demirgüç-Kunt, and Kane (2008)). In this latter, the market could still be efficient if high-quality loans were priced at high prices and low-quality loans were priced at low prices. We now move to testing this hypothesis.

3. Who is a Subprime Borrower?

3.1 Description of Data

The analysis in this paper is based on the Home Mortgage Disclosure Act (HMDA) data from the Federal Reserve. HMDA is a federal home mortgage lending disclosure law that provides comprehensive information on applications for mortgage credit during a calendar year. HMDA applies to banks, bank affiliates and subsidiaries, credit unions, and mortgage companies and finance companies that make home mortgage loans.[3] HMDA requires these lending institutions to disclose information regarding the location, by state, county and census tract of each residential real estate-related loan they made. HMDA also requires these lenders to disclose information about all denied home loan applications.

The first HMDA reporting began in 1991, and each year since, a new HMDA reporting has taken place. The HMDA data used in this paper are for 2004 to 2006 (inclusive). This 3-year period was chosen because in 2004 for the first time lenders were required to report the annual percentage interest rate above the rate charged on a Treasury security of comparable

[3] Exempt from these reporting requirements are non-depository lenders originating less than $25 million of home purchase loans a year.

maturity. The idea is to pick a threshold that is well above average to define higher-priced lending (a.k.a. subprime mortgages). Previous analyses (see, for example, Avery, Brevoort, and Canner (2007)) have accepted the definition of subprime lending as loans with annual percentage interest rates that are at least three percentage points above the rate charged on comparable Treasury securities. This study proposes to examine some consequences of using a different cutoff spread. Our sample period ends in 2006, the latest year for which data are available.

The HMDA files include information on separate reporting institutions for 2004 to 2006. The estimates here combine data on all individual business units within larger corporations or bank holding companies. The rationale for this is as follows: for institutions that are affiliated by common control, and are likely to be doing underwriting in the same way, we wish to treat these individual institutions as one large institution. This combining of business units within larger corporations or bank holding companies reduces the number of separate reporting institutions.

The HMDA data include information on loan applications in 2004, 2005, and 2006. The HMDA files identify five categories of data: loans approved by the lender and accepted by the applicant, loans approved by the lender but not accepted by the applicant, applications denied by the lender, applications withdrawn by the applicant, and files left incomplete by the applicant and reported closed by the lender.[4] For concreteness, we concentrate on applications denied by the lender and loans approved by the lender and either accepted or not accepted by the applicant. This restriction increases the homogeneous of the sample and eliminates the need to model why applicants might withdraw their loan applications or leave their loan

[4] Applications covered by HMDA regulations include requests for a pre-approval in which a lender issues a written commitment to extend a home purchase loan to the applicant up to a specified amount valid for a designated period of time, subject to limited conditions. For the purposes here, we treat requests for pre-approvals no differently than ordinary loan requests.

files incomplete.

The HMDA data report application information on four mortgage loan programs: Federal Housing Administration (FHA) loans, Veterans Administration (VA) loans, Farm Service Agency (FSA) and Rural Housing Service (RHS) loans, and conventional loans. We abstract from FHA/VA and FSA/RHS loan applications, and instead concentrate solely on conventional loans.

HMDA reports information on home purchase loans (usually first time home mortgage loans), home refinancing loans (loans used to replace an existing obligation by the same borrower, in order to lower monthly payments, to pay-off loan sooner, or to cash out; for reporting purposes, both the existing obligation and the new obligation must be secured by liens on dwellings), and home improvement loans (a dwelling-secured loan that is made in whole or in part for home improvement purposes). We concentrate our analysis on both home-purchase and home-refinance lending, while ignoring home-improvement lending.

HMDA lenders must also report whether a loan is subject to the protection of Home Ownership and Equity Protection Act of 1994 (HOEPA), and whether a loan or application involves a one-to-four-family dwelling, or a multifamily dwelling. For this study we limit our attention to all one-to-four dwelling loans, excluding all second mortgages and all high-rate, high-fee (home equity) HOEPA loans which are typically used for home improvements, debt consolidations or other purposes, at the borrower's discretion.

3.2 Odds of Choosing a Subprime Loan

The likelihood of being a subprime borrower is highest for African Americans and Hispanics, controlling for a variety of variables. We establish this result by estimating a very simple logit model relating the choice of a subprime mortgage to various property and borrower characteristics, including race/ethnicity, income as a percent of area median income, gender, census tract income as a percentage of area median income, the racial composition of the neighborhood, state dummy variables (to control for geographical differences in higher-priced lending by state), and a series of dummy variables for whether the loan was sold by the originator, and if so what type of organization purchased the loan. The estimation of a logit form for the probability of being a subprime is consistent with Apgar, Bendimerad, and Essene (2007), and others.

The five definitions of “subprime lending” here discussed include, not only the previous at least three percentage points above the rate charged on comparable Treasury securities, but also four alternatives suggested for exploration: loans with at least four, five, six, and seven percentage points above the rate charged on comparable Treasury securities. In general, the higher the cutoff spread, the fewer the observations – only a small number of first mortgage loans have spreads of seven percentage points or more. It is natural, then, for us to fear the imprecision of defining subprime loans as those having spreads of seven percentage points or more. It is also natural for us to fear using the previous accepted definition of at least three percentage points above the rate charged on comparable Treasury securities, since, historically, there is a 20% chance that mortgages originated by prime lenders could have a spread of at least $2\frac{1}{2}$ percentage points, on average, above the rate charged on a 10-year Treasury security (using data from Freddie Mac’s Primary Mortgage Market Survey, from 1971-2008), a 7% chance that mortgages originated by prime lenders could have a spread of at least 3 percentage points, on average, above the 10-year Treasury security, and a near chance that mortgages originated by prime lenders could have a spread of at least 5 percentage points, on average, above the 10-year Treasury security.[5] For the empirical analyses to follow, we will work with a cutoff spread of five percentage points above the rate charged on comparable Treasury securities. A cutoff spread of five percentage points means that there are about 2.9 million subprime home purchase loans to analyze and 3 million subprime home refinancing loans.

Table 1 presents the means of the variables used in our study, for our one-to-four dwelling based loan sample. Each loan application is treated as an independent observation so that applicants who are denied a loan at one institution but who receive lender approval at a different institution would contribute twice to the sample. The means are presented for the entire sample, as well as separately by borrower type – prime versus subprime. Beginning with our measure of borrower income, we find that subprime borrowers are much more likely to have incomes, but they are also significantly more likely to have high incomes. A possible explanation for this latter observation is that applicants with high incomes are much more likely to be granted a mortgage loan than applicants with low incomes, but at a high price.

It is also obvious from Table 1 that the likelihood of being a subprime borrower is related to martial status. Borrowers who take out subprime loans are on average more likely to be single, widowed, and divorced men and women. This result is not surprising. Numerous studies exist confirming that the living standards of divorcees tend to decline after divorce. For example, Page and Stevens (2002) find that in the long-run family income falls by 40 to 45% and consumption falls by 15 to 20% after divorce; further, while re-marriage following divorce can substantially improve the economic situation for divorcees, the rate of home ownership

[5] Intuitively, if the average spread in Freddie Mac's Primary Mortgage Market Survey is this high, then there is a problem because it means that there are individual mortgages originated by prime lenders with spreads well in excess of, say, $2\frac{1}{2}$ to 3 percentage points above the rate charged on a 10-year Treasury security. This suggests a strong argument for using a cutoff spread in excess of at least 3 percentage points above the rate charged on comparable Treasury securities, but less than 5 percentage points over the 10-year Treasury security.

among divorcees generally tends to be much lower than among couples who did not divorce (i.e., there tends to be more wealth constraints among those previously divorced).

In Tables 2 and 3, we begin to examine the results of a logit analysis of the probability of being a subprime borrower. The results are presented separately by loan type – the estimates in Table 2 are for home-purchase lending, whereas those in Table 3 are for home-refinance lending. For these results, we estimate a cross-sectional regression of the likelihood of being a subprime borrower on seven groups of explanatory variables. All equations are estimated with a known cutoff spread to define subprime mortgages (five percentage points above the rate charged on comparable Treasury securities). t-values are reported in the column labeled t-statistic. Not shown in the table are the parameter estimates for the 0-1 state dummy variables.

Lender	All	Prime	Subprime
Loan Information			
Distribution of Originated Loans by Year			
2004	33.6%	36.1%	7.6%
2005	36.4%	36.2%	38.3%
2006	30.0%	27.8%	54.1%
Loan Amount (in thousands of dollars)	223	226	192
Average spread of Sub-Primes (in bps)	478.9	389.9	606.7
Applicant Information			
Gross Annual Income (in thousands of dollars)	92	94	75
Sex of Applicant(s) (Primary/ Second)			
Male / Male	0.8%	0.9%	0.7%
Male / Female	36.8%	38.3%	20.1%
Male / none	30.2%	29.4%	38.9%
Female / Male	6.8%	6.7%	7.3%
Female / Female	0.8%	0.8%	0.8%
Female / none	24.6%	23.9%	31.9%
Race/Ethnic			
American Indian or Alaska Native	0.9%	0.9%	0.9%
Asian	5.4%	5.6%	2.8%
Black or African American	9.4%	8.0%	24.1%
Native Hawaiian or Other Pacific Islander	0.7%	0.7%	0.7%
Hispanic or Latino	11.8%	11.0%	20.5%
Non Hispanic White	71.7%	73.7%	50.6%
Neighborhood Characteristics			
Percentage of minority population	28.32	27.26	39.49
Percentage of tract income	113.4	114.9	97.7
Type of Purchaser			
Loan was not sold	25.1%	25.6%	19.7%
Fannie Mae (FNMA)	15.2%	16.6%	0.7%
Freddie Mac (FHLMC)	10.3%	11.2%	0.1%
Farmer Mac (FAMC)	0.001%	0.002%	0.003%
Private securitization	5.3%	4.1%	17.8%
Commercial bank	5.4%	5.4%	5.1%
Life insurance company	9.3%	8.5%	18.5%
Affiliate institution	9.7%	9.9%	6.3%
Other type of purchaser	19.8%	18.6%	31.9%

Table 1: Description of HMDA Data, 2004-2007.

Variable	2004 Parameter	2004 t-statistic	2005 Parameter	2005 t-statistic	2006 Parameter	2006 t-statistic
Intercept	0.02	43.18	0.07	62.72	0.16	110.2
H_{MM}	0.004	5.07	0.007	5.14	0.03	15.34
H_M	0.004	24.49	0.04	107.38	0.06	124.14
H_{FM}	0.003	8.03	0.02	27.65	0.03	42.11
H_{FF}	0.002	3.09	0.01	9.01	0.04	19.06
H_F	0.003	14.72	0.04	88.71	0.05	88.71
Native American Borrower	0.004	6.02	0.03	17.44	0.05	21.13
Asian Borrower	-0.003	-11.51	-0.004	-6.15	-0.01	-15.28
Black Borrower	0.03	100.91	0.13	226.14	0.20	282.35
Hawaiian Borrower	0.005	5.97	0.03	14.75	0.05	22.02
Hispanic Borrower	0.006	20.99	0.06	121.79	0.12	193.84
$Income$	-0.00003	-26.23	-0.00008	-43.1	-0.0001	-50.04
$Income^2$	3.90E-09	18.18	1.24E-08	29.45	1.61E-08	33.92
Percent Minority in Census Tract	0.0001	32.58	0.0004	51.92	0.0007	68.29
Relative Income in Census Tract	-0.0001	-51.48	-0.0005	-105.61	-0.0006	-111.89
Portfolio Loan	0.001	3.18	-0.002	-3.05	-0.07	-73.79
Fannie Mae	-0.02	-52.95	-0.07	-95.52	-0.14	-148.18
Freddie Mac	-0.02	-51.5	-0.07	-83.84	-0.13	-131.52
Federal Agricultural Mortgage Corp	-0.02	-1.14	-0.10	-3.76	-0.12	-2.71
Private Securitization	-0.002	-3.31	0.17	200.49	0.25	229.38
Life Company	0.003	6.23	0.06	75.31	0.11	109.05
Affiliate Institution	0.002	5.14	-0.03	-36.16	-0.07	-74.56
Other Purchaser	0.003	8.12	0.06	86.1	0.13	139.03

Table 2: Logistic Model of the Probability of a Subprime Borrower in Home-Purchase Lending, 2004-2006. Logit equations are estimated using home purchase loan observations from the period 2004 to 2006. Subprime loans are defined as those having spreads of at least five percentage points above the rate charged on comparable Treasury securities. t-statistics are reported in the column immediately to the right of the parameter estimates. Not shown in the table are the parameter estimates for the 0-1 state dummy variables. H_{MM} = male applicant with male co-applicant. H_M = male applicant, with no co-applicant. H_{FM} = female applicant, with male co-applicant. H_{FF} = female applicant, with female co-applicant. H_F = female applicant, with no co-applicant. These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

Variable	2004 Parameter	2004 t-statistic	2005 Parameter	2005 t-statistic	2006 Parameter	2006 t-statistic
Intercept	0.04	73.17	0.11	98.3	0.24285	158.93
H_{MM}	0.004	4.87	0.002	0.94	0.00592	2.49
H_M	0.004	18.7	0.03	84.39	0.04101	81.86
H_{FM}	0.01	31.99	0.04	62.02	0.04812	60.3
H_{FF}	0.01	9.83	0.02	12.08	0.03176	14.14
H_F	0.01	25.63	0.03	83.45	0.04028	75.88
Native American Borrower	0.003	3.6	0.009	6.13	0.02184	10.35
Asian Borrower	-0.006	-16.12	-0.01	-15.58	-0.01576	-14.84
Black Borrower	0.03	97.15	0.09	149.32	0.11915	159.38
Hawaiian Borrower	0.002	2.43	0.02	8.96	0.0368	15.81
Hispanic Borrower	-0.002	-7.93	0.03	47.53	0.04946	71.65
$Income$	-0.00005	-40.74	-0.0001	-60.21	-0.00018133	-68.36
$Income^2$	6.65E-09	27.4	1.87E-08	39.68	2.61E-08	43.82
Percent Minority in Census Tract	0.0002	48.1	0.0004	55.25	0.00048062	45.08
Relative Income in Census Tract	-0.0002	-74.99	-0.0005	-111.3	-0.00061776	-96.81
Portfolio Loan	0.002	4.55	-0.01	-14.88	-0.08	-81.57
Fannie Mae	-0.03	-88.19	-0.09	-111.59	-0.19	-174.75
Freddie Mac	-0.03	-80.7	-0.09	-108.64	-0.18	-157.41
Federal Agricultural Mortgage Corp	0.02	0.55	-0.08	-2.40	-0.14	-2.44
Private Securitization	-0.008	-12.34	0.16	180.77	0.20	171.31
Life Company	-0.007	-15.61	0.06	72.57	0.10	95.00
Affiliate Institution	-0.01	-32.17	-0.03	-40.0	-0.08	-72.71
Other Purchaser	0.003	7.56	0.06	83.38	0.08	73.35

Table 3: Logistic Model of the Probability of a Subprime Borrower for Home-Refinance Lending, 2004-2006. Logit equations are estimated using home refinance loan observations from the period 2004 to 2006. Subprime loans are defined as those having spreads of at least five percentage points above the rate charged on comparable Treasury securities. t-statistics are reported in the column immediately to the right of the parameter estimates. Not shown in the table are the parameter estimates for the 0-1 state dummy variables. H_{MM} = male applicant with male co-applicant. H_M = male applicant, with no co-applicant. H_{FM} = female applicant, with male co-applicant. H_{FF} = female applicant, with female co-applicant. H_F = female applicant, with no co-applicant. These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

The estimates in Tables 2 and 3 support several conclusions. First, as indicated in the variable description table above, there are significant racial differences among prime and subprime borrowers. African-Americans are shown to be more likely than whites to be subprime borrowers. For example, when all other covariates except for race are controlled for, African-Americans are more than much more likely than whites to be subprime borrowers. Additionally, the ethnicity results show that Hispanics are much more likely than whites to be subprime borrowers, holding all else equal. These results for African-Americans and Hispanics may be attributable to several factors, including lower income, less wealth, and lower credit scores than whites. Other studies also report substantial racial and ethnic differences in subprime borrowers. See, for example, Apgar, Bendimerad, and Essene (2007).

It also seems that the probability of a subprime borrower is nonlinearly related to income, exhibiting a U-shape, with borrowers at both the high- and low-income ends being much more likely than middle-income borrowers to be subprime. The probability of being a subprime borrower is higher for households headed by singles (i.e., never married, widowed, or divorced) than for married couple households.[6] Gender also has an important influence on the likelihood of being a subprime; the subprime probability for female-headed household is higher than it is for male-headed households.

It is also not unexpected that the probability of a subprime borrower is negatively related to the income of the census tract where the property is located, relative to the overall median income for the MSA, or positively related to the percentage of minority population to total population for the census tract.

We also find that the likelihood of being a subprime borrower is affected by the loan

[6] These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

delivery channel; portfolio loans and loans sold to Fannie Mae and Freddie Mac have a much lower odds of being a subprime mortgage than loans securitized in the private market. This result is consistent with the idea that subprime lenders have better (and cheaper) access to risk capital through the private secondary market than through a diverse array of financing options, including turning to traditional residential mortgage sources, like Fannie Mae and Freddie Mac.

Lastly, we find that the parameter estimate for loans securitized in the private market for 2006 differs significantly from that for 2004, and differs in a positive way. These results are consistent with the notion that as the risk of subprime lending became more widely shared through the private market, access to risky capital became cheaper viz. portfolio lending and sale to Fannie Mae and Freddie Mac.

Next, considering the different cutoff points we examined – from at least three to seven percentage points above the rate charged on comparable Treasury securities – to define subprime lending, we found that the absolute difference in the t-statistics for most explanatory variables generally fell as the cutoff point rose above at least five percentage points (see Table 4). We chose at least five percentage points in part for this reason and partly because of the problems of a small sample that results from choosing a higher cutoff point. Still, none of the results changes qualitatively if we had used a cutoff point of at least three to five percentage points above the rate charged on comparable Treasury securities for defining subprime lending.

	3% cutoff		4% cutoff		6% cutoff		7% cutoff	
Variable	Par	t-value	Par	t-value	Par	t-value	Par	t-value
Intercept	0.26	158.04	0.20	131.38	0.07	65.09	0.01	22.62
H_{MM}	0.05	24.57	0.04	21.55	0.01	6.96	0.001	1.7
H_M	0.09	170.73	0.07	135.41	0.04	90.39	0.10	44.22
H_{FM}	0.05	49.75	0.04	49.11	0.02	23.92	0.003	8.66
H_{FF}	0.05	22.78	0.05	23.11	0.02	12.2	0.005	5.77
H_F	0.07	117.73	0.05	93.18	0.03	66.24	0.007	30.49
Native American Borrower	0.08	31.83	0.06	26.62	0.026	10.37	0.001	1.33
Asian Borrower	-0.02	-19.2	-0.02	-17.31	-0.001	-9.02	-0.002	-6.17
Black Borrower	0.24	295.3	0.23	300.28	0.13	218.1	0.04	125.02
Hawaiian Borrower	0.09	30.75	0.07	25.79	0.02	12.09	0.004	3.09
Hispanic Borrower	0.19	259.37	0.15	228.59	0.05	96.49	0.005	18.27
$Income$	-0.0001	-40.54	-0.0001	-53.25	-0.00009	-45.56	-0.00003	-29.29
$Income^2$	1.52E-08	27.75	1.81E-08	36.28	1.19E-08	30.87	4.55E-09	20.59
Percent Minority in Census Tract	0.0008	68.12	0.0008	70.62	0.0004	50.65	0.0002	37.73
Relative Income in Census Tract	-0.001	-152.4	-0.001	-126.79	-0.0004	-92.3	-0.0001	-55.1
Portfolio Loan	-0.06	-53.94	-0.07	-74.56	-0.03	-41.09	0.002	3.84
Fannie Mae	-0.16	-144.96	-0.16	-162.47	-0.08	-105.29	-0.015	-35.09
Freddie Mac	-0.19	-166.78	-0.16	-152.48	-0.07	-91.23	-0.01	-28.48
Federal Agricultural Mortgage Corp	-0.16	-3.13	-0.15	-3.23	-0.06	-1.73	0.004	0.21
Private Securitization	0.30	235.47	0.29	251.84	0.16	180.56	0.08	150.44
Life Company	0.12	103.79	0.12	110.77	0.05	64.77	0.013	27.42
Affiliate Institution	-0.07	-62.78	-0.08	-74.16	-0.04	-50.39	-0.004	-7.54
Other Purchaser	0.13	124.92	0.14	140.78	0.06	80.85	0.03	66.62

Table 4: Probability of Being a Subprime Borrower assuming Different Cutoff Spreads. Logit equations are estimated using home purchase loans and for 2006 only. Subprime loans are defined as those having spreads of at different cutoff spreads. t-statistics are reported in the column immediately to the right of the parameter estimates. Not shown in the table are the parameter estimates for the 0-1 state dummy variables. H_{MM} = male applicant with male co-applicant. H_M = male applicant, with no co-applicant. H_{FM} = female applicant, with male co-applicant. H_{FF} = female applicant, with female co-applicant. H_F = female applicant, with no co-applicant. These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

4. Lender Fixed Effects

We consider a simple logit framework. Let $y_i^*(t)$ be a latent variable representing the probability that borrower's i loan application was rejected at time t. We assume that $y_i^*(t)$ is a linear function of borrower and neighborhood characteristics, characteristics of the mortgage delivery channel, as well as a series of metro area dummy variables, as given by

$$y_i^*(t) = \beta_0 + \sum_{j=1}^{K} \beta_j x_{ij}(t) + \phi_k(t) + \epsilon_i(t) \tag{1}$$

where $x_{ij}(t)$ is a set of explanatory variables (i.e., borrower and neighborhood characteristics, characteristics of the mortgage delivery channel, etc.) that can be used to predict whether the applicant will be denied the loan at time t, and $\epsilon_i(t)$ is an error term. We do not observe $y_i^*(t)$, but do observe a dummy variable $y_i(t)$ defined by

$$y_i(t) = \begin{cases} 1 & \text{if } y_i^*(t) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Of particular interest for this paper are the lender fixed effects $\phi_k(t)$ in equation (1). The inclusion of fixed effects controls for differences in underwriting standards among lenders. Lenders with looser underwriting standards should have a low $\phi_k(t)$, while lenders with tighter standards should have a high $\phi_k(t)$.

We view it as a virtue that the HMDA data described above can be used to estimate both the likelihood of being a subprime borrower and the probability of being denied a subprime loan. There are some methodological issues that we need to pursue in detail, but (at this stage) have not. One issue deals with the application volume. Our results are obtained without using application volume as a right-hand side variable. In the literature, it is recognized that application volume may affect the loan denial rate. But, then, the loan denial rate may also affect application volume in the neighborhood. Lin (2001) also stresses this; concluding that application volume may be correlated with unobserved dimensions of lenders' actions. In this case, we expect our lender fixed effects to control for some of this unobserved heterogeneity.

Another issue is neighborhood externalities. Lang and Nakamura (1993) argue that the probability of loan acceptance is positively related to the number of recent sales in the neighborhood. The argument goes: loan acceptance is high because as market liquidity improves, lenders become less reluctant to lend in these neighborhoods, and so lend on better terms. Next, these liquidity effects may become self-fulfilling. As loan terms improve, more buyers may wish to enter the market, causing lenders to lend more in these neighborhoods. We do not fully capture this feature. We only control for percent minority and the relative income in each census tract; these census tract variables are used to capture the riskiness of the collateral.

The logit results of explaining the probability that a subprime borrower would be denied a loan are presented in Tables 5 and 6 – the estimates in Table 5 are for home-purchase lending, whereas those in Table 6 are for home-refinance lending. The results presented here suggest that applications from African-Americans and Hispanics have much higher denial rates than applications from whites, all else equal. These results are no different from the Boston Fed study in 1996 (see Munnell et al. (1996)).

Coefficients for the four household types are positive, and significant. These coefficients change little in terms of significance or magnitude over the sample. Avery, Brevoort, and Canner (2007) offer a slightly different account, in which co-applicants, whether male or female, have somewhat lower denial rates than single individuals.

	2004		2005		2006	
Variable	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Intercept	0.10	83.07	0.12	108.47	0.15	121.11
H_{MM}	0.0	26.22	0.05	31.83	0.06	30.19
H_M	0.05	104.06	0.06	132.49	0.07	145.62
H_{FM}	0.03	34.67	0.03	41.7	0.03	37.11
H_{FF}	0.03	17.85	0.04	23.96	0.05	22.85
H_F	0.04	72.92	0.05	98.85	0.06	111.87
Native American Borrower	0.06	37.84	0.06	36.36	0.08	41.24
Asian Borrower	0.02	23.01	0.02	29.79	0.02	19.91
Black Borrower	0.11	152.81	0.11	181.25	0.14	213.53
Hawaiian Borrower	0.04	19.76	0.05	25.41	0.07	29.36
Hispanic Borrower	0.04	68.95	0.05	98.59	0.07	125.19
$Income$	-0.000005	-1.92	0.00001	6.62	0.00006	26.06
$Income^2$	3.26E-09	6.56	1.05E-09	2.31	-5.66E-09	-12.82
Percent Minority in Census Tract	0.0005	55.66	0.0007	79.06	0.0008	87.01
Relative Income in Census Tract	-0.0004	-75.58	-0.0004	-76.47	-0.0004	-75.92
National Banks	-0.009	-13.23	0.005	7.89	-0.05	-64.59
State Member Banks	-0.03	-28.7	-0.060	-73.97	-0.06	-63.09
Non-member Banks	0.007	9.03	-0.03	-42.49	-0.05	-53.98
Credit Unions	-0.03	-22.56	-0.06	-48.88	-0.09	-64.9
Other Lending Institutions	0.002	4.01	-0.02	-36.02	-0.03	-52.69

Table 5: Probability of being Denied a Loan in Home-Purchase Lending, 2004-2006. Logit equations are estimated using home purchase loan observations from the period 2004 to 2006. t-statistics are reported in the column immediately to the right of the parameter estimates. Not shown in the table are the parameter estimates for the lender fixed effects. H_{MM} = male applicant with male co-applicant. H_M = male applicant, with no co-applicant. H_{FM} = female applicant, with male co-applicant. H_{FF} = female applicant, with female co-applicant. H_F = female applicant, with no co-applicant. These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

Variable	2004 Parameter	2004 t-statistic	2005 Parameter	2005 t-statistic	2006 Parameter	2006 t-statistic
Intercept	0.22	193.21	0.28	234.77	0.30	219.09
H_{MM}	0.04	20.84	0.06	30.96	0.07	28.34
H_M	0.07	155.14	0.07	168.94	0.07	136.72
H_{FM}	0.08	117.03	0.09	130.89	0.09	113.97
H_{FF}	0.04	23.76	0.06	28.88	0.07	31.83
H_F	0.04	92.05	0.05	116.04	0.05	91.54
Native American Borrower	0.10	63.78	0.12	71.92	0.13	70.62
Asian Borrower	0.007	8.48	0.02	26.48	0.03	26.05
Black Borrower	0.13	196.74	0.12	189.21	0.11	165.34
Hawaiian Borrower	0.07	37.22	0.07	34.5	0.08	38.05
Hispanic Borrower	0.04	59.89	0.05	73.63	0.05	74.35
$Income$	-0.00004	-15.86	-0.00004	-16.08	-0.00005	-19.36
$Income^2$	1.20E-08	22.26	1.19E-08	22.66	1.22E-08	21.93
Percent Minority in Census Tract	0.00004	3.95	0.00008	8.32	0.00001705	1.69
Relative Income in Census Tract	-0.0009	-164.06	-0.0008	-142.86	-0.00072071	-111.32
National Banks	-0.02	-25.73	-0.01	-14.94	-0.06	-76.26
State Member Banks	0.07	84.72	0.22	320.62	0.22	288.77
Non-member Banks	-0.05	-57.63	-0.10	-112.73	-0.10	-102.38
Credit Unions	-0.11	-90.34	-0.15	-122.9	-0.16	-114.78
Other Lending Institutions	0.15	263.78	0.03	63.92	0.03	46.53

Table 6: Probability of being Denied a Loan for Home-Refinance Lending, 2004-2006. Logit equations are estimated using home refinance loan observations from the period 2004 to 2006. t-statistics are reported in the column immediately to the right of the parameter estimates. Not shown in the table are the parameter estimates for the lender fixed effects. H_{MM} = male applicant with male co-applicant. H_M = male applicant, with no co-applicant. H_{FM} = female applicant, with male co-applicant. H_{FF} = female applicant, with female co-applicant. H_F = female applicant, with no co-applicant. These categories of households were defined by the sexes of the applicant and co-applicant. The base case is considered is male applicant, with female co-applicant.

Lender	2004	2005	2006
JPMorgan Chase Bank	-0.061	-0.134	-0.084
Countrywide Home Loans	-0.032	-0.087	-0.064
H&R Block Mortgage Corporation	0.010	-0.039	-0.036
Credit Suisse Financial Corp	0.088	-0.041	-0.004
Wells Fargo Bank, NA	0.011	0.019	0.016
GMAC Mortgage LLC	0.051	0.055	0.064
Bank of America, N.A.	0.115	0.105	0.099
Capital One N.A.	0.101	0.089	0.117
Washington Mutual Bank	-0.050	-0.054	0.145

Table 7: Average Lender Fixed Effects for Large Subprime Lenders, 2004-2006. Lender fixed effects are estimated in logit equations that include controls for variables that affect the risk of default, those that affect the costs of default, loan characteristics, and personal characteristics of the borrower.

Another pattern that emerges is that loan denial rates are lower, on average, for national and state banks than at other lending institutions (i.e., mortgage brokers, and mortgage bankers). In our analysis, we find very little difference between loan denial rates across home-purchase and home-refinance lending.

Finally, lender fixed effects are significant predictors of loan denial rates in both home-purchase and home-refinance lending. The variation in these fixed effects are shown in Table 7 for the very large subprime lenders. An F-test on these coefficients easily rejects the null hypothesis of no lender fixed effects at the 1% level. Thus, there is strong evidence unobserved lender fixed effects (i.e., underwriting quality) are important are important in the determinants of denial rates on subprime mortgages.

5. Test of Tiering

5.1 Market Pricing of B Pieces

Several recent papers have examined the market pricing of ABSs (see, e.g., Borgman and Flannery (1997), Gorton and Souleles (2005)). Our specification of a pricing equation takes advantage of the panel nature of our data; all BBB-rated notes from subprime ABS issued by the top-25 subprime lenders in the US over the period 2004-2007. The data are from a dataset from Credit Suisse containing the initial yields on all subprime ABSs that were issued during this time period, including the yields on both A and B notes.

We can test the proposition that secondary market investors learn which issuers are delivering high-quality loans and which are not, and that this learning process leads to a tiering between issuers, where the better quality issuers are charged lower ABS spreads, by estimating equations of the following form:

$$Spread_{i,k}(t) = b_0 + b_1 r(t) + b_2 \mu(t) + b_3 \sigma(t) + b_4 \phi_k(t-n) + b_5 Structure_i(t) + e_{i,k}(t) \quad (3)$$

where $Spread_{i,k}(t)$ is the initial spread over the one-month LIBOR on note i from issuer k at time of issuance t. $r(t)$ is the 10-year Treasury rate. $r(t)$ is used to measure a flight-to-quality phenomenon occurring in times of high volatility. This flight-to-quality bids up the prices of treasuries, bids down treasury yields, and causes higher risk premiums (see Vayanos (2004)). We expect the coefficient on $r(t)$ to be negative.

$\mu(t)$ and $\sigma(t)$ are a measure of the percentage change and standard deviation of house prices at time t, respectively. We measure $\mu(t)$ as the growth rate in the Case-Shiller house price index for the US. For $\sigma(t)$, we use a 3-month rolling variance of the Case-Shiller house price index. $\mu(t)$ should enter the pricing equation with a negative sign, as house prices increase, mortgage default risk decreases, and thus $Spread_{i,k}(t)$ should narrow. $\sigma(t)$ should enter the pricing equation with a positive sign, as we see greater house price volatility, $Spread_{i,k}(t)$ should increase.

$Structure_{i,k}(t)$ represents the structure of tranche i at the time of issuance; that is, the degree of subordination and other credit enhancements supporting it. We expect $Spread_{i,k}(t)$ to be a negative function of $Structure_{i,k}(t)$.

The variable representing the lender fixed effects, $\phi_k(t)$, is used to test for evidence of tiering in the pricing of subprime ABSs. Obviously, the measurement of $\phi_k(t)$ poses a continuing problem for secondary market investors. Furthermore, $\phi_k(t)$ should enter the pricing equation with a lag. Experiments were carried out with various lag lengths. Varying the lag length from 6 months to 2 years causes no noticeable change in sign, magnitude, and/or significance level of the coefficient b_4. Thus in what follows, we present results with a lag length of six months.

Table 8 reports the results of our pricing tests. All coefficients have the correct sign and are significant. Note in particular the negative coefficient on $r(t)$. This result supports a flight-to-quality phenomenon in times of high volatility, in which Treasury rates fall while spreads on risky assets increase. Similarly, the growth and volatility in house prices are a significant factor in explaining B-piece spreads, tending to decrease B-piece spreads in a rising market, while increasing spreads in a volatile market.

The coefficient on $Structure_{i,k}(t)$ is both very significant and large. It suggests that the size of the subordination contributes significantly to the B-piece spread. The coefficient on $\phi_k(t)$ has the expected sign and is significant. Indeed, it suggests that subprime lenders with

Variable	Estimates
Intercept	494.41
	(5.72)
$r(t)$	-32.35
	(-1.97)
$\mu(t)$	-7.32
	(-4.88)
$\sigma(t)$	7.41
	(3.75)
$\phi_k(t)$	-71.84
	(-2.70)
$Structure_{i,k}(t)$	-18.57
	(-2.57)

Table 8: Lender Fixed Effects and Initial Spreads on BBB-rated Notes, 2004-2007. The dependent variable is the initial spread on the BBB-rated subprime ABS notes (measured in basis points). Estimation is by OLS. $r(t)$ = the 10-year Treasury rate. $\mu(t)$ = growth rate in Case-Shiller house price index. $\sigma(t)$ = a 3-month rolling variance of the Case-Shiller house price index. $\phi_k(t)$ = lender fixed effects. $Structure_{i,k}(t)$ = the degree of subordination and other credit enhancements supporting it. t-statistics are reported in parentheses.

high (low) loan denial rates had superior (inferior) pricing at origination, a finding which supports the notion of tiered pricing.

5.2 Market Pricing of First-Loss Piece

We now turn to examining the pricing of first-loss pieces in ABSs. To do this, we regress the CDS spread of the ABS issuer on lender fixed effects plus some control variables. More specifically, we estimate the following equation:

$$CDS_k(t) = b_0 + b_1 r(t) + b_2 \mu(t) + b_3 \sigma(t) + b_4 \phi_k(t-n) + e_k(t) \qquad (4)$$

where $CDS_k(t)$ is the issuer's credit default swap spread at time t. $CDS_k(t)$ should reflect issuer default risk at time t; and issuer default risk at time t should reflect (among other things) the credit quality of the subprime residuals held by the issuer. Hence, we postulate that there should be a negative relation between $CDS_k(t)$ and $\phi_k(t-n)$ for issuers of subprime ABSs with a large loan portfolio of subprime residuals; that is, an increase in lender fixed effects (i.e., higher loan denial rates) should reduce issuer default risk, and less issuer default risk should reduce $CDS_k(t)$, holding all else constant.

The regression results are presented in Table 9. The basic data used in these regressions are shown in Figures 5 and 6 (below). The data are monthly, from 2004 to 2007 (and were obtained from Bloomberg). The data include the major lenders in the subprime market for which CDS spreads are readily available, and for which the lender retains some portion of the first-loss piece in their portfolios. Countrywide is one such example. Countrywide services a total loan portfolio of $1.5 trillion, including $110 billion of subprime mortgages. Further, Countrywide holds in its portfolio (or held in its portfolio as of year-end 2007) total interests retained in securitization of $131 million, including $39 million subprime residuals and other related securities.

The spreads in Figures 5 and 6 are interesting. The riskiest home equity issuers have CDS spreads that are, on average, 80 to 300 basis points higher. Compare Figure 5 with Figure 6. We should also note that the sharp rise in the CDS spread for Countrywide in 2005 was primarily the result of derivative accounting problems, similar to the derivative accounting problems at Fannie Mae that significantly reduced their reported earnings. Until the accounting problems surfaced, Countrywide recorded large gains on the sale of mortgage-backed securities that they agreed either to provide protection against extreme changes in

Variable	(1)	(2)
Intercept	115	134.45
	(3.12)	(3.83)
$r(t)$	-15.52	-26.66
	(-2.63)	(-4.87)
$\mu(t)$	0.69	3.44
	(0.71)	(3.89)
$\sigma(t)$	-1.53	-1.52
	(-3.88)	(-3.78)
$\phi_k(t)$	-69.5	–
	(-3.01)	
$Credit_{i,k}(t)$	-2.44	3.27
	(-1.13)	(1.31)
$R_k(t)$	–	3.53
		(2.78)

Table 9: Lender Fixed Effects and the Pricing of the First-Loss Piece, 2004-2007. The dependent variable is the home equity issuer's CDS spread (measured in basis points). Estimation is by OLS. $r(t)$ = the 10-year Treasury rate. $\mu(t)$ = growth rate in Case-Shiller house price index. $\sigma(t)$ = a 3-month rolling variance of the Case-Shiller house price index. $\phi_k(t)$ = lender fixed effects. $Credit_{i,k}(t)$ = 0-1 dummy variable for presence of credit enhancement. $R_k(t)$ = an issuer ranking variable (downgrade in ranking) constructed by looking at ABS loan performance histories. t-statistics are reported in parentheses.

short-term interests or provide safeguards against default, and for which they retained a small portion on their balance sheet.

The results in Table 9 are consistent with the notion of tiering. The coefficient $\phi_k(t)$ coefficient is negative and significant at the 5% (see column (1)). The $r(t)$ and $\mu(t)$ coefficients are also negative and significant (as expected), while the $Credit_{i,k}(t)$ coefficient is negative but is insignificant at the 5% level. The only variable that is difficult to interpret in column (1) of Table 9 is $\sigma(t)$. The sign of $\sigma(t)$ is negative and significant; whereas we expected a positive and significant effect on $CDS_k(t)$.

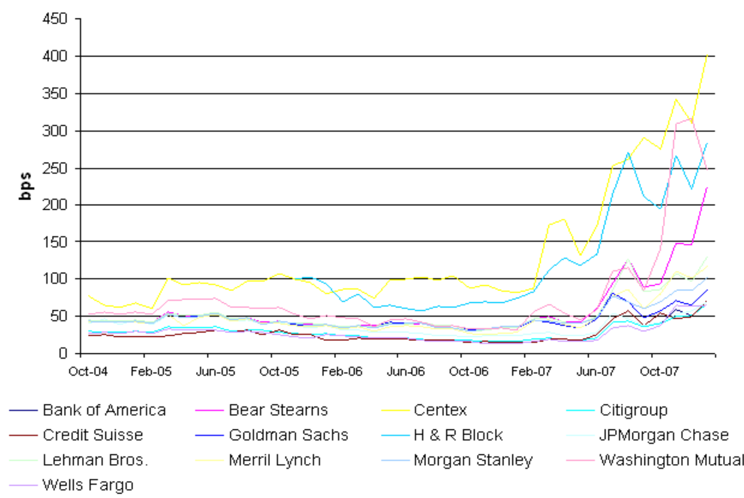

Figure 5: Credit Default Swaps Spreads on Home Equity Issuers. Vertical axis: Swap spread in basis points. Horizontal axis: Time in months. Source: Bloomberg.

We also estimated (4) using $R_k(t)$ as an independent variable replacing $\phi_k(t)$. The results are presented in column (2) of Table 9. Here the results show (as expected) a positive statistical association between $CDS_k(t)$ and $R_k(t)$; that is, downgradings in issuer rankings cause an increase in $CDS_k(t)$. The coefficients of the other variables are stable; although, $r(t)$ is the only other variable with the correct expected sign. Both $\mu(t)$ and $\sigma(t)$ have the wrong signs and are statistically significant, while $Credit_{i,k}(t)$ switches sign from negative to positive but continues to be insignificant.

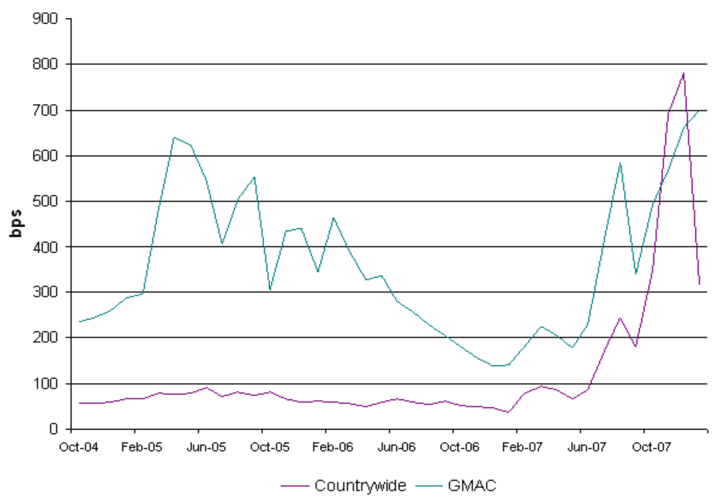

Figure 6: Credit Default Swaps Spreads for Countrywide and GMAC.
Vertical axis: Swap spread in basis points. Horizontal axis: Time in months.
Source: Bloomberg.

6. Concluding Comment

This paper provides evidence that the subprime mortgage market is not a classic lemons market. Ordinarily, in a classic lemons market, informational asymmetries are great and bad products will drive out good products, causing buyers to be unwilling to pay high prices for goods as they expect low-quality goods to be traded. Our results lead to a rejection of this hypothesis, since we find evidence that there are, in fact, differences in the prices of high- and low-quality subprime mortgages.

The analysis focuses entirely on the quality of loans originated and sold in the secondary market by different subprime lenders. In issuing these securities, the originator has historically put himself or herself into a first loss position by holding the lowest priority tranche, thereby enhancing credit for the securitized debt and reducing moral hazard and adverse selection risks. However, these arrangements changed substantially with the growth of the CDO market. Currently, the lowest priority tranches are packaged and used as collateral in a cash-flow CDO, and then these cash-flow CDO tranches are used as collateral in CDO-squared structures. This process of securitization has allowed the underlying subprime mortgage loan cash flows to be apportioned to investors with more congruent risk preferences. But, as the originator's first-loss risk exposure has declined, the risk of moral hazard and adverse selection has increased, and hence there is a possibility for tiered pricing, whereby different subprime lenders would sell enormously different quality of loans to the secondary market. In a lemons market, the effect would be drive out the high-quality loans. In a more efficient market, the effect would be tiered pricing.

In the results reported above, we test for tiering by following the general approach in the literature which consists of setting up a loan denial model, fitting this model to mortgage applications data, finding subprime lenders with high and low (relatively speaking) loan denial rates, and then using these loan denial rates to determine whether there is tiering between issuers.

Our tests lead to an acceptance of the hypothesis of tiering in the subprime mortgage market. An acceptance of this hypothesis is an acceptance of the hypothesis that investors were able to price-discriminate to some extent between high- and low-quality lenders in subprime ABS market. Surprisingly, these results suggest that the subprime ABS market was not doomed to failure with one-sided asymmetric information.

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