After the Honeymoon: Relationship Dynamics Between Mortgage Brokers and Banks

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Abstract

This paper provides new micro-level evidence describing how the dynamics of mortgage broker-bank relationships contributed to the current residential loan crisis. In a theoretical analysis, I demonstrate that brokers have an incentive to present mortgages to the bank that are of decreasing quality over time. Empirically, I find strong evidence of this behavior in the data; I show that 22% of the delinquencies in my data are attributable to the increasing unobservable risk of mortgages originated by a given broker over the course of his relationship with a bank, controlling for month-of-origination vintage effects.

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1 Introduction

A systematic failure in the origination of residential mortgages is one of the causes at the heart of the current credit crisis. This paper provides new micro-level evidence describing how the dynamics of mortgage broker-bank relationships contributed to the dramatic loan default rates currently being observed. In a theoretical analysis, I show that brokers have an incentive to present mortgages to the bank that are of decreasing quality over time. Empirically, I find strong evidence of this behavior in the data, and I show that 22% of the delinquencies in my data are attributable to the increasing unobservable risk of mortgages originated by a given broker over the course of his relationship with a bank. This result controls for both observable loan characteristics and vintage effects on the risk of mortgages originated at different times in the macroeconomic cycle.

There are two plausible models for how relationships between financial intermediaries evolve over time. In the first, as intermediaries come to know each other better, they develop a reservoir a trust and both parties place greater value on the relationship as they interact more frequently. In this model, the unobserved behavior of both parties should improve with time as a cooperative relationship develops. There is, however, an alternative model in which both parties periodically revisit the question of whether to continue the relationship and make a judgement based on their assessment of the past conduct of their counterparty. In this second model, which I develop explicitly in this paper, agents will view early good behavior as crucial, because positive early interactions both enable the relationship to survive the first set of termination assessments and also serve to generate positive information that is used in all the follow-on assessments that occur later. As a result, in the second model, the unobserved behavior of both parties is predicted to be less beneficial to the counterparty as the number of interactions increases. In this paper I present an empirical analysis of the relationship between mortgage brokers and a bank that provides evidence in favor of the second theory; using data on single-family mortgage originations, I show that the unobserved quality of loans generated by a broker and originated by the bank tends to decline over the course of the broker-bank relationship. Comparing the nth loan originated in the broker-bank relationship to the $2n$th, and controlling for all observables available to the bank, I find that the $2n$th loan has a delinquency risk that is 6.4% higher and a foreclosure risk that is 8.1% higher.

All my tests include controls for the month of the origination, so the result describing a decline in unobservable quality does not reflect any macroeconomic trends. I also find that it is the number of interactions, not the length of the relationship in time, that is the key determinant of ex ante unobservable risk. The observable risk characteristics do not change much over the course of a relationship, but it is the case that the increase in unobservable delinquency and foreclosure risk is greatest for the loans with the greatest observable risk.

As the broker-bank relationship evolves, I show that the frequency of interactions increases dramatically: doubling the count of the origination in the broker-bank relationship reduces the time between deals by 27.8 days, which is 77.9% of the mean. Thus, over time, brokers present more loans to the bank, and these loans have higher default probabilities. The decline in unobserved quality over time is not uniform across brokers. In particular, I show that brokers who are more distant from the bank's headquarters experience a more significant increase in unobserved delinquency risk. This may result from higher monitoring costs for distant brokers or from the access of these brokers to their own local banks.

As the relationship progresses, the bank learns more about the broker. The bank makes use of exception pricing to implement risk-based interest rate adjustments. I find that higher exception pricing has greater predictive effects for delinquency later in a relationship. This suggests that the bank becomes more effective in assessing risk as it comes to know the broker better. Nonetheless, this improved information is not sufficient to overcome the negative overall relationship trend towards worse loans.

The bank uses delinquency information to make decisions about relationship termination. The hazard for termination by the bank increases with the average delinquency rate of the previous loans in the relationship. I also find that the termination hazard is decreasing over time: the bank is more reluctant to terminate a long-standing relationship. This finding is somewhat surprising, given the decline that I document in the quality of loans presented by a given broker as the relationship progresses.

Several recent papers have examined the underlying causes of the credit crisis. One stream of this literature considers the effects of securitization on the incentives of mortgage originators (Rajan, 2005, Ashcraft and Shuermann, 2008, Keys et. al, 2008, Mian and Sufi, 2008, Puranandam, 2008).[1] Other work focuses on the decline in lending standards (Dell'Ariccia et al., 2008), manipulation of appraisals (Ben-David, 2009) and the downward trend in loan quality controlling for observables (Demyanyk and Van Hemert, 2008). Benmelech and Dlugosz (2008) and Mason and Rosner (2007) analyze the role of ratings agencies. The role of the subprime component of the market has also received special attention (Gerardi and Willen, 2008 and Foote et al., 2008). Brunnermeir (2008) provides an overview of the crisis.

This paper differs from these studies in its focus on the relationship between mortgage brokers and banks rather than the relationship between banks and the public market for securitized assets. In particular, the loans in my sample were retained by the originating bank, so distortions induced by the securitization process are not relevant in this data. The impact of mortgage broker incentives has been the subject of relatively little empirical analysis (exceptions include LaCour-Little and Chun, 1999 and Keys et. al, 2009). Jiang, Nelson and Vytlacil (2009) show that broker-originated loans were, in general, of lower quality than loans originated by banks themselves. Our focus is on the dynamic development of broker-bank relationships over time. Knoll (1988), Yang and Yavas (1995), Williams (1998) and Garmaise and Moskowitz (2003) discuss

[1]Gabriel and Rosenthal (2007) and Loutskina and Strahan (2008) discuss some of the more positive effects of securitization.

the intermediation role of brokers in real estate in a broader context.

The bank in my data made very few subprime loans (for example, only 0.3% of its borrowers had FICO (Fair Isaac Corporation) credit scores below 620), and, consequently, my results are not driven by that market segment. In essence, I show that default risk for even relatively high quality prime mortgages is related to mortgage broker-bank relationship effects.

The results in this paper add to our understanding of the dynamics of relationship evolution for financial intermediaries, and suggest that in some settings the quality of unobservable behavior may decline in the course of a relationship.

The rest of the paper is organized as follows. Section 2 presents a theory of relationship dynamics between intermediaries and financing institutions. Section 3 details the residential mortgage data that I use to analyze how mortgage broker-bank relationships evolve through time. In Section 4 I outline my econometric approach, and I describe the empirical findings in Section 5. Finally, Section 6 concludes.

2 Model

I model a principal who receives a series of potential projects from an agent. In my empirical application I will view the principal as a bank, the agent as a mortgage broker, and the projects as residential mortgages, but our framework applies equally well to a investment bank receiving prospective IPOs from a venture capitalist, to a bank receiving project financing applications from a firm or to any other long-term relationship between financial institutions. Each project has a binary outcome: success, yielding the principal a payoff of $\pi^s > 0$ and failure, yielding the principal $\pi^f < 0$. The agent receives a fixed commission for each project accepted by the principal.

The are two types of agents, high-quality and low-quality. Agents know their own types, but the principal does not know the agent's type; he has a prior belief that the probability of a high-quality agent is $r \in (0,1)$. Each agent has access to an infinite number of projects. For each project i, ρ_h^i is the probability of a success for a project advanced by a high-quality agent and ρ_l^i is the probability of a success for a project from a low-quality agent. High-quality agents are able to select better versions of each project, so $\rho_h^i > \rho_l^i$. Moreover, I assume that the high-quality agents' superiority in selection is uniformly better across projects. Specifically, I assume that the odds ratio of the high- and low-quality versions of the projects is constant:

$$\frac{\left[\frac{\rho_h^i}{1-\rho_h^i}\right]}{\left[\frac{\rho_l^i}{1-\rho_l^i}\right]} = K > 1 \tag{1}$$

The principal will make inferences about the agent's type by viewing the outcomes of different projects. Assumption (1) guarantees that all projects are equally informative: there are no special projects that are particularly useful for distinguishing between high- and low-quality agents.

I also presume that there is a finite number of good projects. That is, $\rho_h^i \pi^s + (1 - \rho_h^i)\pi^f \geq 0$ for only a finite number of i.

An agent may present projects to the principal in whatever order he chooses. The principal views the outcome of all previous projects and then decides whether or not to accept the current project on offer. The principal is essentially solving a version of the two-armed bandit problem (Berry and Fristedt, 1985), except that in this model the "bandit" is a maximizing agent with asymmetric information. Each agent will choose projects to offer the best possible impression, and the principal's inference process must take the agents' strategies into account.

In the theoretical result, I show that agents always present the best project they have available. As a result, success probability declines over time.

Result 1:

1. Agents present projects with monotonically decreasing success probability over time.

2. The principal terminates an agent when the total number of observed failures at any given point exceeds a time-varying threshold.

A proof is provided in the Appendix.

The intuition underlying the equilibrium may be understood as follows. The agent knows that after each project outcome is realized, the principal will reevaluate the relationship and decide whether or not to continue accepting projects. This is an argument for advancing the best projects early in the relationship, because if the agent initially proposes poor projects, the relationship may simply be terminated and there will be no possibility to ever advance the better projects. Moreover, the constant odds ratio assumption guarantees that the bank will view all project outcomes as equally informative. By presenting the best project he has available, the agent thus accomplishes two aims: first, he increases the probability of surviving the bank's immediate review. Second, even though the agent will later have to present worse projects, the outcome of the earlier projects will still weigh in his favor during later evaluations. Advancing the best projects first ensures that the outcome of these projects will influence the bank's decision during the entire course of a long set of reviews. The weaker projects will only have an impact on the bank's later decisions.

From the bank's perspective, it is simply trying to make an inference about the agent's type given the outcomes of all previous projects. The equal informativeness of all projects allows the bank to focus simply on the total number of successes observed at any point, without concerning itself with the specific history of successes and failures.

3 Data

The data in this paper describe 23,590 residential single-family mortgage loans originated by a U.S. financial institution in the period January 2004- October 2008. Loans made to insiders are excluded. These loans were retained by the bank and not securitized. As described in Table 1, the data include pricing information and details on borrower and property attributes. This bank offers floating rate mortgages, and the mean spread between the loan interest rate and the underlying index is 3.56 percentage points (various indices are used, including the prime rate, the Treasury bill rate and LIBOR). Many of the loans allow borrowers to make payments less than the current interest rate, thereby causing negative amortization. The minimum required payment is determined by the payrate, which has a mean of 2.10 percentage points. The mean loan-to-value (LTV) ratio is 72.1% and the mean borrower FICO credit score is 716.1. This relatively high mean FICO score reflects the fact that the bank made almost no subprime loans (e.g., only 0.3% of borrowers had FICO credit scores below 620). The base interest rate is determined by a fixed set of loan characteristics (LTV, FICO score, etc.), but the underwriters may also adjust the pricing to reflect other perceived risks. The mean of this exception pricing is a relatively small 18.2 basis points.

In common with broader market trends, the bank experienced significant delinquencies and defaults in its residential lending. Specifically, about 13.2% of the loans in the data are delinquent (30 or more days past due) and 7.9% have been foreclosed upon (the foreclosed loans are a subset of the delinquent loans).

Essentially all the residential loans made by the bank are presented to them by mortgage brokers. There are 2,905 different brokers in the data. I track the number of transactions between a given broker and the bank. The mean loan in the sample is the 74th mortgage sent to the bank by that broker. The median loan is the 11th in the relationship, indicating that a small number of brokers have extensive dealings with the bank, while most relationships involve a relatively small number of interactions.

Mortgage brokers who bring loans to the bank are compensated in two ways. First, they receive a rebate (expressed as a fraction of the loan amount) from the bank that is dependent on the loan characteristics. The rebate terms are known to the brokers in advance. The mean rebate I observe is 1.86%. Brokers may also be paid directly by borrowers in a form of compensation known as broker points. Broker points tend to be smaller than the bank-provided rebate: the mean broker points in 0.23% and the median is zero.

Data is also provided on the purpose of the loan (home purchase, cash out refinance or rate/term refinance). Mortgages are further classified by the level of documentation: low documentation loans for which the borrower provides neither income nor asset information, medium-low documentation loans for which the borrower asserts income and asset data without documentation, medium-high documentation loans for which the asset data is documented and high documentation loans for which both income and asset data is documented. A small fraction (1.1%) of loans are provided to depositors in the bank. I also calculate the distances between the bank, the borrower and the broker, using zip code centroid approximations, as street addresses are not provided.

4 Empirical Specification

My main tests focus on changes in the delinquency or foreclosure probabilities of a loan as the mortgage broker-bank relationship progresses. Specifically, I estimate equations of the following form:

$$Default_{i,b,t} = \alpha + \beta * (relationship\, length_{i,b,t}) + \gamma * controls_{i,b,t} + \delta_b + \lambda_t + \epsilon_{i,b,t}, \quad (2)$$

where $Default_{i,b,t}$ is an indicator for whether loan i, provided by broker b in month t subsequently became delinquent, $relationship\, length_{i,b,t}$ is a measure of the length of the mortgage broker-bank relationship at the time of loan origination, $controls_{i,b,t}$ is a vector of loan and property controls including zip code fixed effects, δ_b is broker fixed effect, λ_t is a month fixed effect and $\epsilon_{i,b,t}$ is an error term. In some specifications, $Default_{i,b,t}$ is an indicator for the subsequent foreclosure of loan i.

I estimate (2) using OLS, despite the binary nature of the $Default$ variable, due to the large number of fixed effects along several dimensions (at the broker, month and zip code levels) and the resulting incidental parameters problem in non-linear maximum likelihood estimation (Abrevaya, 1997). OLS coefficients are estimated consistently even with multiple fixed effects. The econometric specification allows for arbitrary correlations over time for each broker. (That is, I cluster at the broker level.) My two primary measures of $relationship\ length_{i,b,t}$ are the log of the loan number (i.e., the log of the count of the current loan in the broker-bank relationship) and an indicator for loans beyond the median loan number in the data (i.e., loans originated after the 11th loan in a relationship).

For some tests, I estimate equations similar to (2) in which the dependent variable is the time elapsed since the previous transaction, the amount of the broker rebate or the pricing of the loan.

To assess the bank's policy on ending broker relationships, I analyze the termination hazard function h (which describes the risk of termination at time s conditional on the relationship still surviving to that time). I estimate the semi-parametric Cox hazard model:

$$h_i(s) = h_0(s)exp(\varphi * controls_i), \tag{3}$$

where $controls_i$ is a vector of controls for loan i (including month of origination) and h_0 is the baseline hazard that the Cox model leaves unspecified. Equation (3) is estimated with clustering at the broker level. The Cox model offers a robust assessment of the impact of the covariates on the hazard rate without requiring an explicit specification of the baseline hazard function.

In some cases, however, the form of the baseline hazard is itself of direct interest. To directly estimate the baseline hazard function, I consider the Weibull parametric hazard function, defining the Weibull probability density function f as

$$f(s) = \frac{\theta s^{(\theta-1)} e^{\frac{-s^{\theta}}{\beta}}}{\beta}. \tag{4}$$

The corresponding hazard function in (3) is given by $h_0(s) = \frac{\theta s^{(\theta-1)}}{\beta}$. I label $(\theta - 1)$ as the shape parameter of this distribution: a positive (negative) shape parameter is associated with an increasing (decreasing) hazard rate.

5 Results

5.1 Relationships and Loan quality

I first consider how the broker-bank relationships develop over time. Specifically, I analyze variation in the performance of loans generated by a specific broker over the course of the relationship by estimating equation (2). I regress via OLS an indicator for eventual delinquency on the log of the loan number and a full set of controls. The controls include the rate spread (which encapsulates the bank's assessment of the loan risk), the pay rate, LTV, borrower FICO score, broker rebate and points, loan purpose indicators (cash out refinance and rate/term refinance dummies), documentation level indicators (dummies for low documentation, medium-low documentation and medium-high documentation loans), an indicator for a borrower who is a depositor, property appraised value and fixed effects for the broker, month of origination (for each of the 58 months in the sample) and property zip code. All standard errors are robust and clustered at the broker level.

The results are displayed in the first column of Table 2. I find that the coefficient on the log of the loan number is positive and significant (t-stat=3.09): controlling for month of origination and borrower and property attributes, loans originated later in a broker-bank relationship are more likely to become delinquent. Doubling the loan number increases the delinquency probability by 85 basis points, which is 6.4% of the mean delinquency risk.

In column two of Table 2, I report results from regressing an indicator for eventual foreclosure on the same set of regressors. I find that log of loan number is positive and significant (t-stat=2.97) in this regression as well. Doubling the loan number increases the foreclosure probability by 64 basis points, which is 8.1% of the mean.

To assess the average impact of relationships on loan performance, I consider the difference between the initial loan in a relationship and the median loan. Moving from the initial loan to the median loan in a relationship increases the delinquency risk by 293 basis points (22.1% of the mean) and the foreclosure risk by 221 basis points (28.0% of the mean).

Any potentially negative information that a broker may have about an application at the time of origination is likely to manifest itself relatively early in the schedule of promised loan repayments. That is, loans viewed as weak by a broker should be particularly likely to result in relatively early delinquencies. I split the loans into early and late delinquencies, using the median loan life for delinquent loans of 863 days as the dividing cutoff. In column three of Table 2, I detail the results from regressing an indicator for early delinquency on the log of the loan number and the previous controls. The coefficient on the log of the loan number is significant (t-stat= 5.23) and large: moving from the initial loan to the median loan increases the risk of an early delinquency by 54.6% of the mean. This indicates that relatively early delinquencies are much more likely to be originated late in a broker-bank relationship.

This finding is not driven by the fact that late in the relationship there is less time between the origination and the end of the data sample - the monthly fixed effects control for this feature of the data. As an illustration, in an untabulated regression of the loan life on the log of the loan number and the controls I find a coefficient on the log of the loan number that is both insignificant (t-stat=0.15) and very small (moving from the initial to the median loan results in an insignificant increase in the loan life of less than 0.4% of the mean). In these regressions there is thus no artificial negative correlation between loan life and the log of the loan number.

In an alternate specification, I consider an indicator for loans originated after the median loan count. As displayed in the fourth, fifth and sixth columns of Table 2, the indicator for post-median deals is also associated with significantly higher delinquency (t-stat=2.14), higher foreclosure probability (t-stat=2.06) and higher probability of early delinquency (t-stat=2.26). A post-median deal has a delinquency risk that is 160 basis points higher (12.1% of the mean), a foreclosure risk that is 115 basis points higher (14.6% of the mean) and an early delinquency risk that is 122 basis points higher (18.5% of the mean).

These findings provide strong evidence in favor of the first prediction of Result 1: the quality of mortgages presented by brokers significantly decreases over time. Moreover, this relationship effect has a large magnitude, explaining roughly one-fifth of the observed delinquencies and foreclosures. This empirical setting, in which securitization did not play a role (the bank retained these loans) and in which almost none of the loans are subprime, makes it possible to isolate the effects of mortgage brokers on residential delinquencies. As the regression results demonstrate, mortgage broker-bank relationship dynamics have a large impact on loan failures, indicating that this nexus played an important role in the evolution of the mortgage crisis.

The results in Table 2 demonstrate that the quality of mortgages generated by the broker and originated by the bank declines as the number of originations increases. Is this relationship effect driven by the number of transactions or by its duration in time? I analyze this question by regressing an indicator for delinquency on the log of the loan number, the log of the relationship duration in days (measured from the first transaction in the data) and the full set of controls. The result, displayed in the first column of Table 3, shows that it is solely the number of transactions that leads to an increase in delinquency risk; duration in time has an insignificant (t-stat=0.19) effect. This makes clear that the nature of a broker-bank relationship is determined by the intensity of interactions, not by the amount of time that has passed since the first deal between the two parties.

The finding that delinquency risk increases over the course of the relationship is *not* driven by macro housing trends over the course of the sample period- the inclusion of fixed effects for every month controls for those trends. To make clear that the relationship-delinquency link is not driven by within-month trends, I regress the delinquency indicator on the log of the loan number, the day of month of the origination and the usual controls. As displayed in the second column of Table 3, the day of month is insignificant and its inclusion has little effect on the coefficient estimate for log of loan number, which remains positive and significant (t-stat=2.98) in this specification as well.

5.2 Loan Characteristics, Relationships and Delinquency Risk

The previous subsection documented a relationship effect in which loan quality declines over the course of the broker-bank interaction. In this subsection, I examine the cross-sectional differences in the relationship effect across various types of loans. Specifically, I regress the delinquency indicator on the log of the loan number, the log of the loan number interacted with the rate spread, the rate spread and the usual controls. As shown in the first column of Table 4, the coefficient on the interaction is positive and significant (t-stat=2.33). This indicates that high rate spread loans, which are in general quite risky, become especially risky late in the relationship between the broker and the bank. For a loan with a rate spread of 3%, moving from an initial loan to a loan with a median count increases the delinquency risk by only 115 basis points, but for a loan with a rate spread of 4% the same increase in loan count increases the delinquency risk by 374 basis points.

I also consider the interaction of the log of the loan number with both the rate spread and the LTV. As shown in the second column of Table 4, both interactions are positive and significant. This indicates that high LTV loans, are particularly likely to lead to delinquency when presented by a broker in a long-established relationship, even when controlling for the impact of the rate spread.

The interaction of the log of the loan number with the borrower's FICO score, as described in the third column of Table 4 is not significant (t-stat=-1.30). The interaction between the log of the loan number and a low-documentation indicator, by contrast, is negative and marginally significant (t-stat=-1.75) (this is shown in the fourth column of Table 4). This suggests that, controlling for the rate spread, low documentation loans actually become somewhat safer later in a relationship.

Taken together, this evidence suggests that high rate spread (and, particularly, high LTV) loans deteriorate most markedly in quality over the course of the broker-bank relationship.

5.3 Deal Flow and Broker Compensation

I now consider how the rate of deal flow evolves over the course of the broker-bank relationship. I calculate the time between the current and previous originations submitted by a given broker, and I then regress this measure on the log of the loan number and the standard controls. As is displayed in the first column of Table 5, I find that the coefficient on the log of the loan number is negative and significant (t-stat=-11.42). Doubling the loan number reduces the time between deals by 27.8 days, 77.9% of the mean. In a second specification, I regress the time between originations on the post-median deal indicator and the controls. In the second column of Table 5, I show that the coefficient on the post-median indicator is also negative and significant (t-stat=-3.92). After the median loan, the time between deals is reduced by 17.9 days, 50.1% of the mean. Overall, these results indicate that the pace of deal flow increases dramatically over the course of the relationship. As the relationship progresses, the broker presents both more and, on average, worse deals. One potential explanation consistent with this evidence is that generating the early high-quality deals requires more of a broker's time. Once these successes have established a broker's reputation, he can focus more on generating quick commissions via less well-screened mortgage applications.

The rebate received by the broker is set by the terms of the bank's posted rebate sheet and determined by observable loan characteristics. It is possible, however, that brokers may "rebate-shop," submitting loans to the bank with the highest rebate. To explore this question, I regress the broker rebate on the log of the loan number and the standard controls other than the rebate itself. The results, given in the third and fourth columns of Table 5, show that there is no statistically significant evidence of increased rebates over time, controlling for loan and property characteristics. The coefficient magnitudes are small, as well. For example, doubling the loan number increases the broker rebate by 0.5 basis points, which is only 0.3% of the mean rebate. Taken together, the evidence on increased rebate shopping over the course of the relationship is weak. The main focus of broker efforts as the relationship progresses appears to be increasing volume, rather than securing favorable pricing.

5.4 Distance and Relationships

Distance can affect the performance of financial intermediaries. I regress the delinquency indicator on the log of the loan number, the log of the distance between the property and the broker and the usual controls. I find an insignificant (t-stat=-0.20) coefficient on the property-broker distance, as I show in the first column of Table 6. This suggests that mortgage brokers do not have specialized knowledge about local properties. In untabulated results, I find no evidence that distance increases over the course of the relationship. To explore the impact of distance on the relationship effect, I regress the delinquency indicator on the log of the loan number, the property-broker distance, the interaction between the two and the full set of controls. The coefficient on the interaction (described in the second column of Table 6) is insignificant (t-stat=-0.25). There is therefore no evidence that the general decline in loan quality is concentrated in properties that are more distant from the broker- it appears not to be the case that brokers seek out more distant low quality loans over time.

One hypothesis is that the relationship effect may be stronger for the most distant brokers, as it is likely more difficult for the bank to monitor them. Moreover, brokers located further from the bank have a broader set of other potential banks to which they can turn if this relationship is terminated, perhaps making them less cautious about forwarding weak applications over time. To test this hypothesis, I regress the delinquency indicator on the log of the loan number, the log of the distance between the bank's headquarters and the broker, the interaction between the two and the controls. For brokers with multiple offices, we use the distance between the headquarters and the office responsible for presenting the loan. The results are detailed in the third column of Table 6. The coefficient on the interaction is positive and significant (t-stat=5.43). This indicates that loan quality deterioration is greater for brokers that are distant from the bank's headquarters. For a broker located at a mean distance from bank headquarters, doubling the loan number increases the delinquency risk by 108 basis points. For a broker located at a mean plus one standard deviation distance from bank headquarters, doubling the loan number increases the delinquency risk by 151 basis points.

Might this finding perhaps be driven by different housing dynamics in markets at varying distances from the bank headquarters? To analyze this question, in the fourth column of Table 6, I display the results from regressing the delinquency indicator on the log of the loan number, the interaction between the log of the loan number and the log of the distance between the property and the headquarters and the controls. (The log of the distance between the property and the headquarters is subsumed into the zip code fixed effects, because I calculate distance using zip code centroids.) The coefficient on the interaction is insignificant (t-stat=1.31). This clearly indicates that it is the distance of the broker, and not the distance of the property, from the bank's headquarters that is most relevant. Variation in local market price dynamics therefore does not explain our finding.

5.5 Bank Screening

In this subsection, I analyze the bank's screening policy. I first consider whether the bank increases the rates on loans originated later in a broker relationship. The bank's underwriters can adjust the posted interest rate for additional risk by applying exception pricing to the mortgage. I regress exception pricing on the log of the loan number and the controls. As shown in the first column of Table 7, the coefficient on the log of the loan number is insignificant. Comparing an initial loan in a relationship to a median loan yields a 1.5 basis point increase in the exception pricing. This is clearly a very small effect, so the evidence is clear that exception pricing does not increase by much over the course of the relationship. It is striking that, despite the significant decline in loan quality as the relationship continues, the bank does not apply larger penalties to the loans presented by the mortgage broker.

In untabulated results, I find that in a regression of the delinquency indicator on exception pricing and the full set of controls, the coefficient on exception pricing is positive and significant (coefficient=0.042, t-stat=2.69). This suggests that exception pricing correctly reflects the bank's assessment that the loan is riskier. To analyze how the bank's information evolves over time, I regress the delinquency indicator on the log of the loan number, exception pricing, the interaction between them and the controls. The results are provided in the second column of Table 7. I find that the coefficient on the interaction is positive and significant (t-stat=2.69). I also regress the foreclosure indicator on the log of the loan number, exception pricing, the interaction between them and the controls. The coefficient on the interaction is positive and significant (t-stat=2.29) in this specification as well. These findings are consistent with the hypothesis that the bank learns more about a broker over time. This increased information leads the bank to charge exception prices that are increasingly correlated with delinquency and foreclosure risks.

These findings support the view that the bank's information does improve with time, an idea found in the relationship banking literature (Sharpe, 1990, Rajan, 1992, Von Thadden, 2004). Despite this learning on the part of the bank, however, the broker nonetheless presents lower quality loans over time.

5.6 Relationship termination

I now turn to the bank's policy in terminating a broker relationship. Using a Cox proportional hazard model (as described in (3), I regress the relationship length (in transactions) on the average delinquency rate of the loans extended and an indicator for whether the last loan was delinquent. The findings, given in the first column of Table 8, show that the hazard termination is significantly increasing (t-stat=6.02) in the number of previously originated loans that eventually become delinquent. This supports the second prediction of Result 1 that relationship termination probability increases in the number of defaults.

For only 1.2% of loans in the data is there a previous loan from that broker that has already entered foreclosure at the time of the origination of the current loan. How, then, can subsequently realized foreclosures be used by the bank to make termination decisions before they are observed? The explanation is that loans that eventually enter foreclosure typically exhibit difficulties (e.g. late payments) earlier in the process, and the bank uses this pre-foreclosure information to evaluate brokers. The coefficient on the eventual delinquency of the last loan is not significant, either because problems with that loan have not yet manifested themselves, or because the average delinquency rate is a sufficient statistic from the bank's perspective.

I also include indicators for eventual delinquency of the second-to-last loan and the first loan in the relationship as additional regressors. As displayed in the second column of Table 8, the estimated coefficients on these regressors are also not significant, providing further evidence that no particular loan is over- or under-weighted in the bank's termination decision. This is consistent with the modeling assumption (1) of a constant odds ratio: each mortgage is apparently viewed by the bank as equally informative about the broker's quality.

As a final test, I estimate a Weibull parametric hazard model, as described in Section 4. The shape parameter describes the evolution of the hazard over time: a positive (negative) shape parameter is associated with an increasing (decreasing) hazard rate. The result from the estimation of the Weibull model is described in the third column of Table 8. I find that the shape parameter is negative and significant (t-stat=-11.68), indicating that the termination hazard is declining in the number of transactions between the bank and the broker. The bank is less likely to terminate the broker as the relationship progresses.

This finding is perhaps surprising, given the strong relationship effect of a decline in loan quality that I document in Table 2. Conditional on a given assessment of overall broker quality, it would be optimal for the bank to increase the probability of termination as the relationship continues, because future prospects dim over time. The results in Table 4 suggest that banks should be especially wary of loans with high observable risk (e.g. high LTV or low FICO scores) that are presented late in a broker-bank relationship.

6 Conclusion

In this paper, I show that unobservable delinquency and foreclosure risks increase over the course of broker-bank relationships, controlling for month of origination. These effects are stronger for more distant brokers and are especially pronounced for mortgages with higher rate spreads and loan-to-value ratios. Over time, the pace of deal flow from a given broker increases markedly, even as the quality declines. The increase in unobservable risk takes place even though the bank becomes more successful in risk assessment as the relationship progresses. I find that approximately one-fifth of the observed delinquency and foreclosure rates in the data are attributable to broker-bank dynamics, suggesting that these relationship effects were an important component of the current mortgage crisis.

The interaction between mortgage brokers and banks is an ideal context for studying relationship effects because of the large number of relatively homogenous mortgages with well-documented observable risk characteristics that each broker presents. The findings in this paper, however, have application to any market in which agents interact with known counterparties and develop relationships. Examples include venture capitalists and investment banks, asset managers and investors, and corporations and commercial banks. In all these cases, our theory and empirical results suggest that a long-standing relationship may be associated with worse, rather than better, unobservable behavior.

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Appendix

Proof of Result 1: I begin by assuming that agents adopt the strategy described in the result of presenting projects in declining order of success probability. I now consider the bank's optimal response. I denote the number of good projects for the high-quality agent by T. Clearly, the bank will reject all projects advanced beyond the first T. Once the bank has rejected a project, it will not update its assessment of the quality of the agent, and the presented projects are declining in success probability, so it will reject all subsequent projects.

I denote a history of all the previous project outcomes up to period t by the t-tuple $hist^t$, representing successes with ones and failures with zeros. If the bank is still considering projects when the Tth project is presented, it faces a choice between rejecting the project and receiving zero or accepting the project and receiving an expected retention payoff rp of

$$rp(hist^T) = \left(\rho_h^T \pi^s + (1-\rho_h^T)\pi^f\right) P(type = h|hist^T) \tag{5}$$

$$+ \left(\rho_l^T \pi^s + (1-\rho_l^T)\pi^f\right)(1 - P(type = h|hist^T)).$$

I define $c(hist^t)$ to be the principal's continuation payoff after a given history $hist^t$. I have $c(hist^T) = max\{rp(hist^T), 0\}$. I can now define c recursively for any history. This gives

$$rp(hist^t) = \left(\rho_h^t(\pi^s + c(hist^t, 1)) + (1-\rho_h^t)(\pi^f + c(hist^t, 0))\right) P(type = h|hist^t) \tag{6}$$

$$+ \left(\rho_l^t(\pi^s + c(hist^t, 1)) + (1-\rho_l^t)(\pi^f + c(hist^t, 0))\right)(1 - P(type = h|hist^T)).$$

Rejecting the project is also an option, so $c(hist^t) = max\{rp(hist^t), 0\}$.

Using Bayes' Rule, for any t I can calculate

$$P(type = h|hist^t) = \frac{P(hist^t|type = h)P(type = h)}{P(hist^t|type = h)P(type = h) + P(hist^t|type = l)P(type = l)}$$

$$= \frac{r}{r + (1-r)\frac{P(hist^t|type=l)}{P(hist^t|type=h)}}.$$

and

$$\frac{P(hist^t|type=l)}{P(hist^t|type=h)} = \prod_{i=1}^{t}\left(\frac{1-\rho_l^i}{1-\rho_h^i}\right)\left[\frac{\rho_l^i(1-\rho_h^i)}{\rho_h^i(1-\rho_l^i)}\right]^{hist^t(i)}. \tag{7}$$

I will now show that if $P(type = h|hist_a^t) \geq P(type = h|hist_b^t)$ then $c(hist_a^t) \geq c(hist_b^t)$. This is true for any history of length T by (5). I now proceed by recursion. It is sufficient to show that $c(hist_a^t, 1) \geq c(hist_b^t, 1)$, $c(hist_a^t, 0) \geq c(hist_b^t, 0)$ and $c(hist_a^t, 1) \geq c(hist_a^t, 0)$, and the result will then follow from (6). To see that $c(hist_a^t, 1) \geq c(hist_b^t, 1)$, note that

$$\frac{P((hist_a^t,1)|type=l)}{P((hist_a^t,1)|type=h)} = \prod_{i=1}^{t}\left(\frac{1-\rho_l^i}{1-\rho_h^i}\right)\left[\frac{\rho_l^i(1-\rho_h^i)}{\rho_h^i(1-\rho_l^i)}\right]^{hist_a^t(i)}\frac{\rho_l^{t+1}}{\rho_h^{t+1}}$$

$$\leq \prod_{i=1}^{t}\left(\frac{1-\rho_l^i}{1-\rho_h^i}\right)\left[\frac{\rho_l^i(1-\rho_h^i)}{\rho_h^i(1-\rho_l^i)}\right]^{hist_b^t(i)}\frac{\rho_l^{t+1}}{\rho_h^{t+1}} = \frac{P((hist_b^t,1)|type=l)}{P((hist_b^t,1)|type=h)},$$

where the inequality follows from $P(type = h|hist_a^t) \geq P(type = h|hist_b^t)$. By (7), $P(type = h|(hist_a^t, 1)) \geq P((type = h|hist_b^t, 1))$, so the recursion step shows that $c(hist_a^t, 1) \geq c(hist_b^t, 1)$. An analogous argument shows that $c(hist_a^t, 0) \geq c(hist_b^t, 0)$, and $c(hist_a^t, 1) \geq c(hist_a^t, 0)$ follows from a similar argument and the fact that $\frac{\rho_l^{t+1}}{\rho_h^{t+1}} \leq \frac{1-\rho_l^{t+1}}{1-\rho_h^{t+1}}$.

The constant odds ratio assumption and (7) show that the conditional probability that the agent is type h (and hence, the probability that the principal accepts project $t+1$) depends only the sum of success up to period t. It is also clear from (7) that $P(type = h|hist^t)$ is increasing in $\sum_i^t hist^t(i)$. I may thus define a sequence $\{thresh_t\}_{t=1}^T$ of thresholds, such that project $t+1$ is accepted by the principal if and only if $\sum_i^t hist^t(i) \geq thresh_t$ (and if all previous projects have been accepted).

I now consider an agent's optimal response to this bank policy. The agent receives a constant payoff for each project accepted, so the agent maximizes

$$\sum_{j=1}^{T} P\left(\cap_{t=1}^{j}\{\sum_{i=1}^{t} hist^t(i) \geq thresh_t\}\right). \tag{8}$$

Every strategy choice by an agent induces a distribution over the realization of the project outcomes. I denote the outcome of project t by X_t, where a success is one and a failure is zero. I can thus rewrite (8) as

$$\sum_{j=1}^{T} P\left(\cap_{t=1}^{j}\{\sum_{i=1}^{t} X_i \geq thresh_t\}\right). \tag{9}$$

I first show that an agent will only select the T projects with the highest success probabilities and that the agent's optimal strategy will be independent of the history of realized successes and failures. I denote the agent's project choice in period t by $\hat{C}_t$ and the history of choices up to period by C_t. An agent's strategy describes his choice $\hat{C}_t$ as a function of $(C_t, hist^t)$. For any $\hat{C}_T(C_T, hist^T)$, I claim that the agent can improve his payoff by choosing as his T-period project the good project with the highest success probability that is excluded from C_T.

Suppose instead that the agent's strategy involves choosing a weak project with success probability p^1 and the strategy does not choose the good project with the highest success probability $p^2 \geq p^1$. For each project with success probability p_j, success will occur if a Uniform[0,1] random variable $w \leq p_j$. I denote the Lebesgue measure by μ. For a sequence of projects with length t, the probability of success is given by

$$\mu\left(w \in [0,1]^t : \cap_{i=1}^{t}\{\sum_{j=1}^{i} I_{w(j) \leq p_j} \geq thresh_i\}\right). \tag{10}$$

Replacing the weak project with the highest success probability project weakly increases the set of w meeting the restriction in (10) because $I_{w(j)\leq p^1} \leq I_{w(j)\leq p^2}$ for any $w(j)$.

I will now proceed by induction to prove that the agent's optimal strategy will include only good projects and will be history-independent. This was just shown for the for base case $t = T$. The induction hypothesis is that for any $(C_t, hist^t)$ the subsequent agent strategy (denoted by $C_{t,+}$) uses only good projects and is independent of any outcome in period t or thereafter. For any $\hat{C_{t-1}}(C_{t-1}, hist^{t-1})$ replace the proposed subsequent strategy $C_{t-1,+}$ with whichever of $C_{t-1,+}((C_{t-1}, \hat{C_{t-1}}), (hist^{t-1}, 1))$ and $C_{t-1,+}((C_{t-1}, \hat{C_{t-1}}), (hist^{t-1}, 0))$ yields the agent a higher expected payoff. Then replace $\hat{C_{t-1}}$ with the highest success probability good project that is not included in $C_{t-1,+}$ or C_{t-1}. By the argument given above, this revised strategy will yield the agent a higher payoff. Last, in the event of randomization, maximize over all possible $\hat{C_{t-1}}(C_{t-1}, hist^{t-1})$ (with subsequent strategies chosen as just described) and choose the one $\hat{C^*_{t-1}}$ with the highest expected payoff for the agent. Then define $C_{t-1,+}(C_{t-1}, hist^{t-1}) = (\hat{C^*_{t-1}}, C_{t-1,+})$. This new strategy is superior to any candidate strategy, uses only good projects and does not depend on any outcome in period $t-1$ or thereafter. The result follows by induction.

I now show that the agent will advance projects in declining probability of success. By the work above, we need only consider candidate strategies that use only good projects and are history independent. Suppose that under a candidate strategy project $(t+1)$ has success probability p_1 (denote by Y) and project $(t+2)$ has probability $p_2 \geq p_1$ (denote by Z). Consider a strategy that switches the order of the two projects. By the argument given above, for the first $(t+1)$ outcomes, the switched strategy yields a weakly higher probability of project acceptance at each stage than the original strategy. Now consider $s \geq t+2$. Under the original strategy, the probability of project acceptance at the s -stage is

$$P(\cap_{t=1}^{i}\{\sum_{i=1}^{t} X_i \geq thresh_t\} \cap \{\sum_{i=1}^{t} X_i + Y \geq thresh_{t+1}\}$$

$$\cap\{\sum_{i=1}^{t} X_i + Y + Z \geq thresh_{t+2}\} \cap_{t=i+2}^{s} \{\sum_{i=1}^{t} X_i + Y + Z + \sum_{i=t+1}^{T} X_i \geq thresh_t\})$$

$$:= P(B)$$

Under the switched strategy, the probability of project acceptance at the s -stage is

$$P(\cap_{t=1}^{i}\{\sum_{i=1}^{t} X_i \geq thresh_t\} \cap \{\sum_{i=1}^{t} X_i + Z \geq thresh_{t+1}\}$$

$$\cap\{\sum_{i=1}^{t} X_i + Z + Y \geq thresh_{t+2}\} \cap_{t=i+2}^{s} \{\sum_{i=1}^{t} X_i + Y + Z + \sum_{i=t+1}^{T} X_i \geq thresh_t\})$$

$$:= P(C)$$

For $A \in \{B, C\}$, I can decompose:

$$P(A) = P(A|Y=1, Z=1)P(Y=1, Z=1) + P(A|Y=1, Z=0)P(Y=1, Z=0)$$

$$+P(A|Y=0, Z=1)P(Y=0, Z=1) + P(A|Y=0, Z=0)P(Y=0, Z=0)$$

I note that $P(B|Y=1, Z=1) = P(C|Y=1, Z=1)$ and $P(B|Y=0, Z=0) = P(C|Y=0, Z=0)$. Moreover,

$$P(C|Y=0,Z=1) = P(B|Y=1,Z=0) \geq P(B|Y=0,Z=1) = P(C|Y=1,Z=0).$$

The result that the expected payoff for the agent is higher under the switched strategy then follows from the fact that $P(Y=0,Z=1) = (1-p_1)p_2 \geq (1-p_2)p_1 = P(Y=1,Z=0)$. Thus, switching projects so that the higher success probability project is selected first always weakly increases the agent's payoff. It follows that a strategy of selecting projects in declining success order is optimal.

Table 1:
Summary Statistics

Variable	Mean	Median	Standard Deviation	$1^{st}\%$	$99^{th}\%$
Rate spread	3.56	3.6	0.53	2.25	4.68
Pay rate	2.10	1.95	1.01	0.5	5.98
LTV	0.72	0.78	0.14	0.27	0.95
FICO Score	716.06	713	44.22	626	806
Broker Rebate	1.84	2	0.84	0	3.25
Broker Points	0.23	0	0.49	0	2
Delinquent	0.13	0	0.34	0	1
Foreclosed	0.08	0	0.27	0	1
Loan Number	74.46	11	167.38	1	880
Cash out refinance	0.67	1	0.47	0	1
Rate refinance	0.15	0	0.36	0	1
Low doc	0.14	0	0.35	0	1
Med-low doc	0.32	0	0.47	0	1
Med-high doc	0.29	0	0.45	0	1
Depositor	0.01	0	0.10	0	1
Exception Pricing	0.18	0.1	0.37	-0.43	1.25
Property-Broker Distance	69.56	23	116.91	0	441.76
Property-Headquarters Distance	169.23	117.69	139.15	4.81	392.79
Broker-Headquarters Distance	157.25	91.3	139.12	3.49	370.57
Time Between Deals	35.71	8	86.97	0	448

Table 2:
Mortgage Broker-Bank Relationships and Loan Quality

Results from the regressions of an indicator for whether a bank loan became delinquent (first and third columns) and an indicator for whether a bank loan led to a foreclosure (second and fourth columns) on relationship variables, transaction attributes and property variables.

Dependent variable	Delinquent?	Foreclosed?	Early Delinquency?	Delinquent?	Foreclosed?	Early Delinquency?
N	*21,564*	*21,564*	*21,564*	*21,564*	*21,564*	*21,564*
Log(Loan No.)	0.0122	0.0092	0.0150			
	(3.09)	(2.97)	(5.23)			
Post-Median Deal				0.0160	0.0115	0.0122
				(2.14)	(2.06)	(2.26)
Rate spread	0.0253	0.0456	0.0381	0.0256	0.0417	0.0382
	(2.52)	(5.98)	(5.26)	(2.43)	(5.21)	(5.28)
Pay rate	-0.0064	-0.0105	-0.0091	-0.0135	-0.0192	-0.0088
	(-1.18)	(-2.85)	(-2.55)	(-2.38)	(-4.47)	(-2.44)
LTV	0.2779	0.1551	0.1289	0.0953	0.0332	0.1273
	(14.87)	(12.94)	(11.36)	(3.24)	(1.77)	(11.20)
FICO Score	-0.0005	-0.0003	-0.0003	-0.0005	-0.0003	-0.0003
	(-9.88)	(-6.78)	(-7.33)	(-2.61)	(-2.03)	(-7.38)
Broker Rebate	-0.0122	-0.0203	-0.0106	-0.0097	-0.0158	-0.0108
	(-2.05)	(-4.07)	(-2.59)	(-1.54)	(-3.10)	(-2.61)
Broker Points	-0.0083	-0.0101	-0.0125	-0.0085	-0.0106	-0.0125
	(-1.12)	(-1.68)	(-2.11)	(-1.15)	(-1.76)	(-2.11)
Cash out refinance	-0.0145	-0.0172	-0.0083	-0.0080	-0.0108	-0.0083
	(-1.98)	(-2.56)	(-1.47)	(-1.08)	(-1.65)	(-1.48)
Rate refinance	0.0204	0.0143	0.0253	0.0258	0.0201	0.0249
	(2.11)	(1.76)	(3.46)	(2.67)	(2.45)	(3.42)
Low doc	0.0427	0.0093	0.0205	0.0517	0.0197	0.0204
	(4.60)	(1.17)	(2.85)	(5.20)	(2.30)	(2.87)
Med-low doc	0.0331	0.0004	0.0153	0.0433	0.0108	0.0154
	(4.66)	(0.07)	(2.82)	(5.79)	(1.81)	(2.87)
Med-high doc	0.0399	0.0212	0.0206	0.0458	0.0258	0.0209
	(5.52)	(3.77)	(4.09)	(6.34)	(4.53)	(4.16)
Depositor	-0.0236	-0.0092	-0.0227	-0.0226	-0.0098	-0.0237
	(-1.11)	(-0.74)	(-2.02)	(-1.08)	(-0.79)	(-2.12)
Fixed effects?						
Zip Code	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Broker	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.30	0.28	0.31	0.25	0.28	0.31

Table 3:

Number of Interactions, Duration of Relationship and Day of Month Effects

Results from the regressions of an indicator for whether a bank loan became delinquent on relationship variables, day of month, transaction attributes and property variables.

Dependent variable	Delinquent?	Delinquent?
N	*21,564*	*21,564*
Log(Loan No.)	0.0113	0.0120
	(2.33)	(2.98)
Log(duration)	0.0005	
	(0.19)	
Origination Day of Month		-0.0001
		(-0.34)
Rate spread	0.0255	0.0255
	(2.42)	(2.42)
Pay rate	-0.0139	-0.0139
	(-2.44)	(-2.45)
LTV	0.0967	0.0968
	(3.29)	(3.30)
FICO Score	-0.0004	-0.0004
	(-2.56)	(-2.56)
Broker Rebate	-0.0095	-0.0095
	(-1.52)	(-1.52)
Broker Points	-0.0084	-0.0084
	(-1.13)	(-1.12)
Cash out refinance	-0.0080	-0.0079
	(-1.07)	(-1.07)
Rate refinance	0.0260	0.0261
	(2.69)	(2.70)
Low doc	0.0520	0.0520
	(5.22)	(5.22)
Med-low doc	0.0434	0.0433
	(5.81)	(5.81)
Med-high doc	0.0457	0.0457
	(6.34)	(6.33)
Depositor	-0.0218	-0.0217
	(-1.05)	(-1.04)
Fixed effects?		
Zip Code	Yes	Yes
Month	Yes	Yes
Broker	Yes	Yes
R^2	0.33	0.33

Table 4:
Loan Characteristics, Relationships and Delinquency Risk

Results from the regressions of an indicator for whether a bank loan became delinquent on relationship variables, transaction attributes and property variables.

Dependent variable	Delinquent?	Delinquent?	Delinquent?	Delinquent?
N	*21,564*	*21,564*	*21,564*	*21,564*
Log(Loan No.)	-0.0276	-0.0466	-0.0013	-0.0296
	(-1.58)	(-1.99)	(-0.06)	(-1.63)
Rate*Log(Loan No.)	0.0108	0.0099	0.0106	0.0117
	(2.33)	(2.26)	(2.31)	(2.36)
LTV*Log(Loan No.)		0.0306		
		(1.97)		
FICO*Log(Loan No.)			0.0000	
			(-1.30)	
(Low Doc)*Log(Loan No.)				-0.0070
				(-1.75)
Rate spread	-0.0076	-0.0049	-0.0072	-0.0101
	(-0.47)	(-0.31)	(-0.45)	(-0.60)
Pay rate	-0.0063	-0.0062	-0.0062	-0.0060
	(-1.14)	(-1.13)	(-1.12)	(-1.09)
LTV	0.2747	0.1914	0.2743	0.2753
	(14.16)	(4.78)	(14.16)	(14.17)
FICO Score	-0.0006	-0.0005	-0.0005	-0.0006
	(-9.92)	(-9.92)	(-5.03)	(-9.93)
Broker Rebate	-0.0105	-0.0105	-0.0106	-0.0106
	(-1.77)	(-1.76)	(-1.77)	(-1.79)
Broker Points	-0.0084	-0.0082	-0.0086	-0.0078
	(-1.13)	(-1.10)	(-1.15)	(-1.06)
Cash out refinance	-0.0164	-0.0174	-0.0163	-0.0165
	(-2.24)	(-2.36)	(-2.22)	(-2.24)
Rate refinance	0.0189	0.0176	0.0190	0.0188
	(1.96)	(1.84)	(1.98)	(1.95)
Low doc	0.0430	0.0427	0.0429	0.0639
	(4.66)	(4.65)	(4.65)	(4.35)
Med-low doc	0.0338	0.0336	0.0337	0.0337
	(4.74)	(4.70)	(4.72)	(4.71)
Med-high doc	0.0408	0.0407	0.0407	0.0405
	(5.68)	(5.69)	(5.68)	(5.66)
Depositor	-0.0223	-0.0228	-0.0227	-0.0228
	(-1.06)	(-1.09)	(-1.08)	(-1.08)
Fixed effects?				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Broker	Yes	Yes	Yes	Yes
R^2	0.32	0.33	0.32	0.33

Table 5:

Deal Flow and Broker Compensation Over Time

Results from the regressions of the time between the current transaction and the previous one (columns one and two) and broker rebate compensation (columns three and four) on relationship variables, transaction attributes and property variables.

Dependent variable	Time Between Deals	Time Between Deals	Broker Rebate	Broker Rebate
N	*18,801*	*18,801*	*21,564*	*21,564*
Log(Loan No.)	-40.1372		-0.0071	
	(-11.42)		(-0.89)	
Post-Median Deal		-17.8754		0.0069
		(-3.92)		(0.56)
Rate spread	-2.2847	-2.3805	0.6281	0.6280
	(-1.03)	(-1.05)	(14.87)	(14.86)
Pay rate	0.7122	-0.3953	-0.1284	-0.1286
	(0.43)	(-0.24)	(-10.05)	(-10.06)
LTV	14.3904	18.9086	-0.4259	-0.4252
	(1.56)	(1.92)	(-7.12)	(-7.09)
FICO Score	0.1076	0.1110	0.0001	0.0001
	(2.26)	(2.22)	(0.21)	(0.22)
Broker Rebate	-2.0664	-1.6206		
	(-1.30)	(-0.96)		
Broker Points	-0.7560	-0.7621	-0.1035	-0.1037
	(-0.27)	(-0.27)	(-8.94)	(-9.00)
Cash out refinance	2.0447	2.2720	-0.0212	-0.0213
	(1.24)	(1.33)	(-2.11)	(-2.12)
Rate refinance	0.9786	2.1805	-0.0251	-0.0249
	(0.45)	(0.95)	(-2.01)	(-2.00)
Low doc	-1.3077	-1.1864	-0.6322	-0.6323
	(-0.57)	(-0.50)	(-23.89)	(-23.92)
Med-low doc	-0.2533	-0.9088	-0.3961	-0.3962
	(-0.14)	(-0.48)	(-23.10)	(-23.13)
Med-high doc	-0.7105	-1.3179	-0.1405	-0.1407
	(-0.40)	(-0.73)	(-11.46)	(-11.47)
Depositor	-6.6552	-6.6953	0.0060	0.0067
	(-0.74)	(-0.73)	(0.15)	(0.17)
Fixed effects?				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Broker	Yes	Yes	Yes	Yes
R^2	0.65	0.65	0.81	0.82

Table 6:
Distance and Relationships

Results from the regressions of an indicator for whether a bank loan became delinquent on relationship variables, transaction attributes and property variables.

Dependent variable	Delinquent?	Delinquent?	Delinquent?	Delinquent?
N	*19,959*	*19,959*	*19,959*	*19,959*
Log(Loan No.)	0.0134	0.0146	-0.0345	0.0018
	(3.12)	(2.40)	(-3.83)	(0.20)
Property-Broker (P-B) Distance	-0.0005	0.0005		
	(-0.20)	(0.14)		
P-B Distance*Log(Loan No.)		-0.0004		
		(-0.25)		
HQ-Broker (HQ-B) Distance			0.0426	
			(1.47)	
HQ-B Distance*Log(Loan No.)			0.0099	
			(5.43)	
HQ-P Distance*Log(Loan No.)				0.0022
				(1.31)
Rate spread	0.0224	0.0223	0.0246	0.0236
	(1.99)	(1.98)	(2.30)	(2.18)
Pay rate	-0.0155	-0.0155	-0.0150	-0.0144
	(-2.50)	(-2.50)	(-2.51)	(-2.45)
LTV	0.0999	0.0998	0.1077	0.0892
	(3.47)	(3.48)	(3.74)	(3.04)
FICO Score	-0.0005	-0.0005	-0.0005	-0.0005
	(-2.86)	(-2.85)	(-2.83)	(-2.81)
Broker Rebate	-0.0085	-0.0085	-0.0093	-0.0078
	(-1.30)	(-1.30)	(-1.48)	(-1.24)
Broker Points	-0.0050	-0.0051	-0.0040	-0.0075
	(-0.64)	(-0.65)	(-0.52)	(-1.01)
Cash out refinance	-0.0050	-0.0050	-0.0053	-0.0080
	(-0.61)	(-0.61)	(-0.69)	(-1.02)
Rate refinance	0.0283	0.0283	0.0275	0.0271
	(2.88)	(2.88)	(2.84)	(2.74)
Low doc	0.0499	0.0499	0.0518	0.0507
	(4.77)	(4.78)	(5.14)	(4.98)
Med-low doc	0.0385	0.0385	0.0410	0.0418
	(4.98)	(4.98)	(5.45)	(5.51)
Med-high doc	0.0451	0.0451	0.0447	0.0472
	(5.91)	(5.91)	(5.97)	(6.41)
Depositor	-0.0152	-0.0151	-0.0157	-0.0228
	(-0.71)	(-0.71)	(-0.74)	(-1.10)
Fixed effects?				
Zip Code	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Broker	Yes	Yes	Yes	Yes
R^2	0.30	0.30	0.30	0.30

Table 7:
Bank Screening

Results from the regressions of exception pricing by the bank (column one), an indicator for whether a bank loan became delinquent (column two) and an indicator for whether a bank loan led to a foreclosed (column three) on relationship variables, transaction attributes and property variables.

Dependent variable	Exception Pricing	Delinquent? Pricing	Foreclosed?
N	*21,564*	*21,564*	*21,564*
Log(Loan No.)	0.0061	0.0100	0.0077
	(1.61)	(2.51)	(2.48)
Except. Pricing*Log(Loan No.)		0.0131	0.0091
		(2.69)	(2.29)
Except. Pricing		-0.0437	-0.0414
		(-2.08)	(-2.87)
Rate spread		0.0296	0.0504
		(2.28)	(6.16)
Pay rate	0.2462	-0.0139	-0.0182
	(22.54)	(-2.30)	(-3.95)
LTV	0.4594	0.0964	0.0365
	(13.43)	(3.26)	(1.91)
FICO Score	-0.0002	-0.0004	-0.0002
	(-1.11)	(-2.56)	(-1.98)
Broker Rebate	-0.0451	-0.0101	-0.0181
	(-7.12)	(-1.58)	(-3.56)
Broker Points	0.0106	-0.0088	-0.0108
	(1.77)	(-1.18)	(-1.78)
Cash out refinance	0.0256	-0.0078	-0.0105
	(4.52)	(-1.06)	(-1.63)
Rate refinance	0.0197	0.0260	0.0204
	(2.54)	(2.70)	(2.50)
Low doc	0.3597	0.0522	0.0218
	(32.16)	(5.02)	(2.40)
Med-low doc	0.1024	0.0441	0.0117
	(11.84)	(5.87)	(1.98)
Med-high doc	0.0890	0.0451	0.0256
	(12.60)	(6.30)	(4.46)
Depositor	-0.0424	-0.0220	-0.0094
	(-2.01)	(-1.06)	(-0.77)
Fixed effects?			
Zip Code	Yes	Yes	Yes
Month	Yes	Yes	Yes
Broker	Yes	Yes	Yes
R^2	0.73	0.33	0.28

Table 8:

Relationship Termination

Results from regressing the length of the broker-bank relationship (in number of transactions) on relationship variables and transaction attributes. Results from the Cox proportional hazard model are presented in columns one and two, and results from the Weibull parametric hazard model are presented in column three.

Dependent variable	Number of Loans	Number of Loans	Number of Loans
N	*22,821*	*22,821*	*22,821*
Avg. Delinquency Rate	2.5152	3.7559	2.6091
	(6.02)	(4.77)	(6.69)
Last loan delinquent	0.0746	0.1234	
	(0.49)	(0.71)	
2nd-to-last loan delinquent		-0.3162	
		(-1.55)	
First loan delinquent		-0.3296	
		(-0.81)	
Shape Parameter			-0.5651
			(-11.68)
Fixed effects?			
Month	Yes	Yes	Yes