Nonlinear Incentives and Mortgage Officers' Decisions

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Abstract

In the aftermath of the recent financial crisis, banks should ensure that their incentive compensation policies appropriately balance long-term risk with short-term rewards. Using daily output data from mortgage officers in a US commercial bank, we test the notion that nonlinear contracts create time-varying incentives for the employees and impose costs on the firm. We provide empirical evidence that mortgage officers greatly increase their output towards the end of each month, when the minimum monthly quota is assessed. This occurs through a combination of reducing the processing time and approving some marginal applications. We also find that mortgages originated on the last working day of the month have a higher likelihood of delinquency.

Keywords: Nonlinear incentives, hurdle, effort gaming.
JEL Classifications: G21, J33, M52

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"[...] Poorly designed compensation policies can create perverse incentives that can ultimately jeopardize the health of the banking organization." [1]

Ben Bernanke, Chairman of the Federal Reserve

1. Introduction

In the aftermath of the recent financial crisis, a source of systemic risk was identified in the banking sector's compensation practices, both for senior executives and large groups of non-executive employees with common incentive structures.[2] The extant financial literature has focused on banks' executive compensation, thus offering little, if any, insights on issues related to the compensation of non-executive employees. This paper attempts to fill in the void by presenting robust empirical evidence on the aggregate outcome of mortgage officers that are subject to nonlinear incentives.

Although mortgage officers should optimally be compensated based on the loan performance, the combination of long maturities in household lending and exogenous shocks on debtors renders such contract design impractical (Baker, 2000). Moreover, banks have historically characterized mortgage officers as administrators rather than salespeople, exempting them from the overtime requirements of the Fair Labor Standards Act. The US Department of Labor only recently challenged this notion by clarifying that mortgage officers are not administrators, but production employees having the primary duty of sales.[3]

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[1] Excerpt from a speech to the Independent Community Bankers of America's National Convention (Phoenix, AZ - 3/20/2009).

[2] See the OCC/OTS/FED/FDIC interagency press release on the finalized "*Guidance on Sound Incentive Compensation Policies*" (Federal Register: 6/25/2010, Volume 75, Number 122). Similar guidance is also offered at the international level by the Financial Stability Board in a report titled "*Thematic Review on Compensation*" (3/30/2010).

[3] See Fair Labor Standards Act [FLSA Section 13(a)(1), 29 U.S.C., § 213(a)(1)] and US Dept. of Labor - Wage and Hour Division (WHD) Administrator's Interpretation No. 2010-1. This interpretation marks a reversal from previous guidance on the topic, namely WHD's Opinion Letters FLSA2006-31 and 2001-WL1558764.

In the absence of a consensus on the second-best contract and the job's nature, banks have long utilized a variety of incentive designs. Several banks have used nonlinear incentives, although this type of incentives may not be appropriate for mortgage officers. While there is some evidence that firms typically opt for nonlinear incentives in a sales context in order to attract overconfident employees (Larkin and Leider, 2011), it is neither clear that mortgage officers can be characterized as conventional salespeople, nor that overconfidence is desirable for household banking operations.[4] Moreover, across employment settings, nonlinear incentives are found to occasionally motivate counter-productive behavior (Healy, 1985; Jensen, 2003; Jensen et al., 2004), which may not be appropriate for banks due to their systemic footprint.

From a theoretical perspective, nonlinear incentives present a special case of organizational incentives that occasionally lead to unintended consequences. Holmstrom and Milgrom (1987) predict that, in a repeated moral hazard framework with nonlinear contracts, an agent's incentives change across time depending on her cumulative output to date. They also argue that a nonlinear contract imposes costs to the principal to the extent that a linear contract is more efficient than a nonlinear one. The purpose of this paper is to empirically test these two predictions utilizing the case of mortgage officers in a US commercial bank who face a minimum output quota at the end of each month.

We analyze loan origination timing and loan performance, and discuss how nonlinear incentive contracts could drive mortgage officers to vary the quantity and quality of originated loans within each month. We find strong evidence that mortgage officers substantially vary their output during the length of each month. The magnitude of the monthly time series variation in mortgage officers' output is economically significant. In particular, towards the end of each month, mortgage officers are increasing their aggregate output by reducing their processing time and approving some

[4] Notably, overconfidence has been shown to adversely affect firm performance in a variety of employment contexts (Landier and Thesmar, 2009; Malmendier and Tate 2005).

marginal applications. This pattern is immediately reversed in the beginning of the next month, and is persistent across all months in our three-year sample. We also confirm the presence of adverse effects on the firm since the loans originated at the end of each month have an increased likelihood of becoming delinquent compared to loans originated in the remaining days of the month.

Our results are consistent with previous empirical evidence on nonlinear contracts creating history-dependent incentives. Asch (1990) finds that navy recruiters vary their effort in an attempt to win awards, by having higher output in the months immediately prior to becoming eligible to win a prize. Addressing the nonlinear incentive contracts for salespeople and executives, Oyer (1998) illustrates that manufacturing firms' sales monotonically increase throughout the year, reaching their highest level at the end of the fiscal year. In a similar fashion, Larkin (2007) uses data from a leading enterprise software vendor and finds that its salespeople game their performance by closing the majority of their deals on the last day of each quarter. This performance gaming results in excess customer discounts representing 6-8% of vendor revenue. Importantly, a common finding across the aforementioned empirical studies on nonlinear contracts is that the performance spikes at the end of each period. This should be expected for the employees since meeting the output hurdle early in the period would result in an upward revision of their assigned hurdle by their employer.[5]

We offer a novel insight into the incentive structures of the mortgage industry. Despite the wide interest in housing markets, the topic of mortgage officers' compensation has been sparsely studied.[6] This study focuses on household mortgages

[5] Alternatively, a behavioral explanation would attribute this particular performance pattern to procrastination. In deciding between leisure and effort, while lacking the theorized exponential-utility discounting, employees have present-biased preferences, thus procrastinating to avoid immediate costs. Interestingly, procrastination can survive even in the presence of deadlines or sophisticated individuals, while learning -in a repeated framework- is plausible but slow (O'Donoghue and Rabin, 1999*a*, 1999*b*).

[6] There are two recent studies on commercial loan officers that are tangentially related to this study. In the first study, Hertzberg et al. (2010) illustrates that commercial loan officers reduce their optimistic bias when the threat of rotation becomes imminent. In a similar fashion, Agarwal and Wang (2009) find that commercial loan officers in a US commercial bank dramatically increased their output after the

and offers a unique look at officers' incentives since these loans occur with high frequency, are singularly assigned to a mortgage officer, and there is no post-decision interaction between borrower and officer. Also, since the vast majority of mortgage applications in our sample are fully documented, the mortgage officer can manipulate her effort to a greater extent than she can manipulate the quality of the application (the opposite is true for decisions based on soft information, such as those for commercial loans).

This paper contributes to the incentives literature in a number of ways. First, we use high-frequency data on perfectly observed daily aggregate outcomes over the course of three years, while the nonlinear incentives are monthly, rather than quarterly (Asch, 1990; Larkin, 2007) or annual (Oyer, 1998).[7] Moreover, rather than focusing solely on the effort-gaming aspect of nonlinear incentives, we also offer unique evidence on the extent to which nonlinear aspects of employment contracts may distort future firm performance, thereby introducing a tradeoff between quantity and quality through the examination of loan performance.[8] In this sense, the findings in our study offer mortgage officers' nonlinear incentives as an additional explanation, albeit minor, for poor mortgage portfolio performance and suggest that widespread usage of nonlinear incentives for mortgage officers across banks may have systemic risk implications. This

bank changed their incentive package from fixed wage to fixed wage plus commission. However, the quality of these loans was considerably reduced and the bank soon reverted to the previous incentive structure. Overall, these two studies illustrate the sensitivity of output quality to incentive structures and organizational measures. A common thread behind these findings is that they study commercial lending that rely heavily on soft information (i.e., signals that cannot be verified ex-post), thus allowing loan officers to manipulate their cases in order to increase their compensation. Moreover, commercial loans are rather infrequent and often involve a team of officers thus making it difficult to distinguish individual effort.

[7] The focus of this study is the firm-level (aggregate) consequences of widely-used nonlinear incentives. From a parametric viewpoint, an analysis at the individual mortgage officer level would not be feasible given the small number of loans that each officer processes every month, as well as the processing heterogeneity across mortgages. In order to exemplify this point, the only study of nonlinear incentives' effect on individual workers focuses on a small number of workers having the repetitive task of feeding hundreds of checks into a sorting machine each day (Copeland and Monnet, 2009). Also, that study describes a notable amount of worker turnover, which is induced by low-levels of job satisfaction and not by missing the performance hurdle of the nonlinear contract.

[8] Existing studies take the output as given without considering the possibility of reversal in the output quality, e.g., cancelled/modified sales agreements (Oyer, 1998), poor recruit quality and retention (Asch, 1990), and discounts that may lead to higher customer loyalty in the future (Larkin, 2007).

last point is particularly important in light of financial regulators' current effort to improve compensation practices that expands beyond the senior executives to also include groups of employees, which are subject to similar incentive structure and -in aggregate- may expose the financial institution to material amounts of risk.

The remainder of the paper proceeds as follows: Section 2 reviews the institutional background and describes the hypotheses. Section 3 outlines the data, while Section 4 presents the empirical strategy and the results. Section 5 argues against borrower preferences as an alternative explanation for the results. Section 6 concludes.

2. Institutional Background and Hypotheses

The commercial bank studied in this paper has designed its mortgage officers' compensation with the stated objectives of maximizing the number of loan originations and the profitability of the mortgage unit. In particular, mortgage officers in the bank, throughout the 2006-08 period, are typically paid through commissions for the loans originated every month.[9] At the same time, these officers are subject to a monthly minimum output quota.[10] Those failing to meet the quota for three consecutive months are subject to disciplinary action, including dismissal. Notably, any deficit in a monthly quota is carried over to the subsequent month, thus augmenting that month's quota. Also, disciplinary action can result at the end of a single month (not three consecutive months) if the mortgage officer fails to meet the quota by a large margin.[11]

[9] The bank has a strict limit for overages/underages. Failure to comply with these strict limits for overages/underages results in disciplinary action for the mortgage officer. Hence, overages/underages are more-or-less constant across loan originations, and we can safely consider them as an additive part to the commission. Also, a number of other minor incentives/adjustments exist but their contribution in the officers' compensation is quite minor. Furthermore, in order to retain the best mortgage officers, the bank offers an annual productivity bonus to those officers whose annual loan output exceeds a pre-specified number of mortgages or cumulative loan amount.

[10] This quota may vary across mortgage officers based on some criteria, such as experience.

[11] This is a particularly severe penalty compared to nonlinear contracts described in earlier studies. For instance, in Larkin (2007), a salesperson with zero sales would still earn $12,000.

Unlike fixed and linear incentives, the aforementioned nonlinear aspect operates as a penalty device for poor performers by imposing a hurdle for each officer's monthly output. Linear incentives intend to motivate the mortgage officer after she meets the minimum quota. This combination of linear and nonlinear incentives aims to reduce moral hazard and to align productivity with earnings (i.e., number of originations to monthly income). However, the monthly output hurdle could allow for time-varying effort (Gibbons, 2005). Furthermore, these incentives focus solely on loan originations and are not linked to loans' future performance, thus potentially allowing the mortgage officers to trade-off quantity with quality (Baker, 2000). Although the bank's underwriting guidelines require a minimum loan quality, mortgage officers may have some discretion on approving marginal applications by allowing risk-based pricing to account for variations in applicant creditworthiness. Moreover, it is not unusual for mortgage officers to receive exceptions from their supervisors, who have their own sales goals at the unit level, in favor of marginal applicants on various grounds.[12] Importantly, employees who are not mortgage officers, but are involved in the mortgage process, receive either a fixed salary or a fixed salary plus a performance incentive. This performance incentive is minor compared to the fixed salary and is actualized only at high levels of productivity, which is measured in terms of all mortgage applications processed, not just originations.

Besides the presence of the monthly output hurdle, it is important to mention other aspects of the mortgage officers' employment setting that are related to our study. During our sample period (2006-2008) for the bank's retail lending, the number of mortgage officers and the number of branches remained relatively stable.[13] At the same time, there was very limited mobility of mortgage officers among branches, and the mortgage officers specialize in household properties, thus spending most of their time in

[12] An example of such exceptions is when the applicant has been a long-time customer of the bank.
[13] The exact numbers cannot be revealed to protect the identity of the bank.

an office. Typically, mortgage officers work a five-day, forty-hour week, and are not restricted in the number of customers they choose to service.[14] Also, employment growth for mortgage officers is average, with limited opportunities for promotion to a managerial position. This lack of vertical mobility may have been exacerbated during the housing boom, as a result of the increased origination opportunities. In this way, mortgage officers seem to operate in a repeated contract setting that is very different from promotion-based incentives (e.g., *up-or-out* models). Since the incentive structures did not change during our sample period (except for some minor adjustments in the slope of the linear contract at various intervals after the output hurdle), any output fluctuation can be attributed to the productivity of the incumbent workforce rather than sorting effects from outflow/inflow of high-productivity officers (Lazear, 2000).

Notably, the reward schedule after the hurdle does not have a cap. Instead, the commission rates increase considerably across output buckets, creating a strong disincentive for a mortgage officer to withhold originations for the next month. Also, once submitted, loan applications cannot be reassigned across mortgage officers. Although some loan characteristics in applications are stationary within each month (e.g., loan amount, lien status), most of the characteristics are non-stationary (e.g., debt-to-income ratio, credit score, product), especially in localities with lower application volumes.

The aforementioned institutional environment illustrates an intertemporal moral hazard problem, closely resembling several aspects of the Holstrom and Milgrom (1987) framework. Mortgage officers' actions are frequent within each period and their sequence of actions affects a corresponding sequence of outcomes. Also, all past outcomes are observed before the next day's action is chosen. The principal observes the outcomes at the end of each period, and the nonlinear aspect of the contract is confined only at the

[14] See the detailed job description for mortgage officers by the Bureau of Labor Statistics (O*NET 13-2072.00).

hurdle which serves to identify low-performers and dissuade officers from slacking. Additionally, mortgage officers' strategy space is enhanced given that each period prior to the performance hurdle has about twenty-one working days. Moreover, the assumption of an exponential utility function is likely since the frequency of mortgage originations allow for the officers' annual income not to be dramatically affected by variations in the daily outcome, and thus any income variations are small relative to the officers' risk tolerance.[15] Interestingly, despite the frequent repetition of the principal-agent relationship, a step-function contract (see Mirrlees, 1974) is not feasible due to the difficulty of accurately predicting the exogenous variation in the demand for loans. Overall, the theoretical framework on gaming aspects of nonlinear incentives offers the empirical prediction that mortgage officers vary their performance within each month.

Our hypotheses are tested in three consecutive stages. In the first stage, we verify the presence of time-dependent output, i.e., an end-of-month productivity effect. That effect would be manifested by a significant increase in the number of originations towards the last working day of the month, in order to meet the monthly hurdle. Notably, since the mortgage officers are rewarded only for originations, we do not expect the number of denials to be time-dependent. In the second stage, upon confirming the aforementioned hypothesis, we examine whether this end-of-month monthly spike in mortgage officers' originations is due to increased effort or due to approving loans that are on the margin. The former would be manifested by a quicker processing time for loan applications originated towards the end of the month. The latter would be manifested if approved borrowers at the end of the month have marginally lower creditworthiness. We hypothesize the magnitude of the effect to be small due to the limited discretion of mortgage officers as a result of hard information and mostly

[15] See Lal and Srinivasan (1993) for a detailed discussion of the 'exponential utility function' assumption in the case of salespersons facing nonlinear incentives.

automated underwriting systems.[16] We also test whether mortgage officers increase originations by offering more favorable pricing towards the end of the month in order to entice approved borrowers to accept the offer. Finally, in the third stage we examine the presence of adverse firm effects, in terms of lower loan performance, as a result of this incentive design. We expect to find higher levels of delinquency among loans that were originated at the end of the month since they include these marginally approved applications.

3. Data

We utilize successive Home Mortgage Disclosure Act (HMDA) datasets of a bank during the 2006-2008 period, enriched with additional applicant- and loan-specific variables (known as HMDA Plus).[17] These additional variables are not publicly available, and as a result of confidentiality provisions we cannot identify the bank. We concentrate on the retail lending (vis-à-vis wholesale/correspondent lending), since we study the aggregate behavior of mortgage officers, rather than brokers/correspondents.[18] Also, since mortgage officers (and most closing agents) have a 5-day workweek we seldom observe loan activity during the weekend or national holidays, and for this reason we drop any closing dates that were observed during weekends and national holidays (<0.5% of the sample).[19] Similarly, we exclude completed loan applications that took more than five months to close (3.5% of the sample). These prolonged closing times are somewhat

[16] It is important to mention that even these automated underwriting systems identify marginal cases and produce an 'approve/refer with caution' recommendation, thus allowing some discretion to the mortgage officer in the decision process.

[17] HMDA data consist of loan-level information, including action date, on every residential mortgage application or purchase by a bank during a calendar year. Complete documentation for the data can be found at http://www.ffiec.gov/hmda/

[18] This study cannot be extended to brokers' activity for two reasons: (a) unlike mortgage officers who are subject to a uniform bank-wide compensation policy, brokers' compensation varies dramatically across brokerage firms; and (b) compared to established lenders, brokerage firms are far more flexible when it comes to overages/underages, thus offering a substantial source of additional compensation, which is loosely correlated with loan volume.

[19] The vast majority of weekends and national holidays have zero originations due to the particular employment arrangements for mortgage officers. Hence, the inclusion of weekends and national holidays in our sample would distort the regression estimates.

extreme cases, indicating either an erroneous date entry or underwriters having difficulties obtaining the necessary documents or borrowers altering aspects of their application; in either case, these observations could potentially skew the results and thus are dropped from the final sample. Regarding loan purpose, we keep loans for home purchases and refinance, but we exclude applications for home improvement because they follow different procedures and have a much smaller contribution to the mortgage officers' incentives. Moreover, home improvement applications are only 1.5% of all home mortgage applications in the retail lending during our sample period, while the typical loan amount in these applications is only a fraction of the respective one in applications for home purchase or refinance. The final sample consists of 568,027 completed loan applications during the 2006-2008 period with the following outcomes: originated, approved/not-accepted, or denied. Table 1 contains detailed information on the sample's descriptive statistics.

Figures 1-4 illustrate the daily variation in mortgage decisions in the bank across three years, marking the last working day of each month with a dot. We find that mortgage decisions spike exactly on the last working day of each month throughout the three years (Figure 1). This spike can be solely attributed to originations (Figure 2), since the daily number of either declined applications (Figure 3) or approved/not-accepted applications (Figure 4) does not seem to exhibit any periodic seasonality.[20] Also, there is no apparent periodicity in the demand for loans, as reflected in the volume of submitted applications, which could have explained the end-of-month spike in originations (Figure 5). Similarly, there is little variation in the average loan amount of approved loans on a daily basis throughout the 2006-2008 period (Figure 6), implying

[20] Figure 4 depicts the sharp decrease of approved/not-accepted applications after April 2008. This change accurately reflects the fact that, with the financial crisis and the dramatic decline in housing prices after the fourth quarter of 2007, many prospective borrowers stopped shopping across lenders for better rates, while it was less likely for approved applicants to loose their bid for a specific property.

that -on aggregate- mortgage officers' time-variant behavior is reflected only in the number of originations.

Loan performance data are taken from the OCC Mortgage Metrics dataset (hereafter, OCCMM), covering loan performance from January 2008 until March 2011.[21] Because the field specifying origination channel in the OCCMM data is over-inclusive and may contain loans from non-retail lending channels (primarily purchased/serviced loans), we merge the OCCMM data with the bank's retail HMDA Plus data covering all retail originations from 2006 to 2008. This merging ensures that we are only assessing the performance of loans originated by loan officers in the bank's retail lending. To secure unique matches, the datasets are matched on ten criteria: institution, originating channel, closing date, loan amount, credit score at origination, loan-to-value ratio at origination, occupancy status, lien status, product type and property location (i.e., State). The final dataset consists of 388,300 loans, or 89% of the originated loans in our HMDA Plus sample of the bank's retail lending during 2006-2008. Thus, the sample of matched mortgages is quite representative of the bank's retail lending (see Table 1, Columns 2 and 5), and can offer important insights into the performance of loans at the institutional level.

Throughout this paper, we define delinquency using the standard definition of 60 days (or more) past due on payment, including default events, such as deed-in-lieu of foreclosure, short sale and foreclosure. The reason for choosing this delinquency threshold is the low cure rate for mortgages that become 60 days delinquent. Also, in order to simplify the analysis, we group together current loans and loans that were fully prepaid, due to refinance or property sale. This is intuitive from a lender's perspective

[21] OCCMM is a proprietary dataset that is similar to the LPS Applied Analytics dataset, which is commercially available (www.lpsvcs.com). All the variables used in our paper are available in the LPS dataset. LPS was formerly known as McDash data. Also, in an earlier version of this paper, we had a 73% matching rate between HMDAplus and OCCMM because an earlier version of OCCMM did not include performance of mortgages with a subordinate lien.

given the sharp difference between the default cost and the prepayment cost, especially in the presence of contractual prepayment penalties and institutional liquidity constraints. In other words, even though both events of interest (prepayment and delinquency) result in mortgage termination, they may not be considered to be competing risks in a strict sense since they do not produce a comparable failure, while the dependency between these two events is not straightforward.[22]

Although OCCMM monitors performance starting in January 2008, this dataset includes information on whether a specific loan in our sample is already in default process in January 2008. Given the lengthy process for foreclosures and short-sales, we effectively capture almost all of the seriously delinquent loans during year 2007. Prior to 2007, the options of refinancing or prepayment through sale were readily available to struggling borrowers as a result of the rising property prices. Based on the aforementioned, there are very few seriously delinquent loans originated during the 2006-2008 period whose delinquency is not captured in our dataset.

For the purposes of predicting delinquency, we consider the payment history up to Match 2011, thus offering an average of 45 months loan performance history (Min: 27 months, Max: 63 months). This time period is sufficient for reliable inference since mortgage delinquency follows a hazard function with the rate of increase in conditional delinquency rates decreasing across time. Figure 7 illustrates the cumulative delinquency rates for our sample of loans grouped into six-month periods based on closing date. Differences across these loan groups reflect changes in underwriting requirements and local economic conditions across time. As an example, the cumulative delinquency rate after 36 months for loans originated in the second half of 2007 is 27%, compared to only 14% for loans originated in the first half of 2008. Notably, these cumulative delinquency

[22] At the aggregate level the cost of these two outcomes may be similar when the prepayment rate is much higher than that of delinquency, thus allowing for a competing risks framework. For instance, Deng et al. (2000) use a sample of Freddie Mac loans originated during the 1976-1983 period, where the cumulative prepayment and default rates four years after origination are 60% and 4%, respectively. Obviously, this is not the case for loans originated during our sample period.

rates contrast those of the lender analyzed in Jiang et al. (2011: Figure 2), which relied on lower quality, reduced-documentation loans. For instance, in Jiang et al. (2011) the cumulative delinquency rate after 36 months for loans originated in the second half of 2006 is 33%, compared to 20% for loans originated during the same period in our dataset.

4. Empirical Strategy and Results

4.1. Volume of loan decisions

In identifying intra-month variation on daily volume of loan decisions, we replicate the specification widely utilized in financial economics where calendar dummies address seasonal factors and Newey-West (1987) errors correct for potential heteroskedasticity and autocorrelation:

$$Y_t = \alpha_0 + \beta \text{Distance} + \gamma \text{Month}_t + \delta \text{Year}_t + \lambda \mathit{Controls}_t + \varepsilon_t \qquad [1]$$

where the dependent variable Y at time t interchangeably represents the aggregate output (counts) of originated loans, denied loans and approved-not-accepted loans. Also, *Month* and *Year* correspond to vectors with month and year fixed effects, respectively, whereas *Distance* denotes a vector of dummies indicating the distance at time t in days from the last working day of the month, ranging between zero and thirty.[23] This distance measure effectively provides an end-of-month indicator (when distance equals zero) as well as dummies for the remaining working days of the month, while addressing the fact that the last working day of the month varies depending on the length of the month and the weekends. In addition, the *Distance* vector also captures possible trends in the effect within each month. We add controls for the number of submitted applications during a period of twenty days (between t and t-*19)*, as well as their mean credit score, loan-to-value ratio and debt-to-income ratio, in order to address possible

[23] We opt to use this distance measure rather than day-specific dummies because the last working day of the month often varies across months, due to uneven monthly counts, weekends and national holidays.

variation in aggregate workload, applicant creditworthiness and loan characteristics across time.

Table 2 presents regression estimates from specification [1] quantifying the aforementioned illustrations in Figures 2-4. The end-of-month indicator is highly positive and statistically significant for the case of originated loans. More specifically, we find that on the last working day of the month there is a 301% increase in originations compared to the first working day of each month, which serves as the omitted dummy (Column 1).[24] Even if we exclude the non-end-of-month day-specific fixed effects, effectively comparing the last working day of the month to the rest of the month, we still find that the volume of originations is 233% higher than the average daily level of originations throughout the remaining working days of the month (Column 2). In contrast, we obtain insignificant results, either statistically or economically, for denied applications (Columns 3-4) and for applications that were approved by the mortgage officer but not accepted by the borrower (Columns 5-6). Notably, only the end-of-month effect on originations persists in alternative estimation methods such as censured regression or quantile regression.

Going back to the case of originations, it is important to mention the gradual nature of the day effects leading up to the last working day of each month. This gradual effect is best illustrated in Figure 8, where we plot the estimated coefficients for the *Distance* vector from Table 2, Column 1.[25] Zero distance denotes the last working day of the month, while the maximum distance is thirty days. There is a statistically significant increase in originations during the last week of each month, becoming

[24] This effect is calculated as (e^{β}-1), where β is the coefficient estimate for the respective End-of-Month indicator.

[25] Recall that the variables refer to the distance between a specific working day in the month and the last working day in that month. Also, when plotting the estimated coefficients for the *Distance* vector from Table 2, Columns 3 and 5 we find no time-specific pattern for denied applications and approved-not-accepted applications.

markedly steeper on the last working day of the month.[26] Finally, the sheer magnitude of the increase in 'end-of-month' originations suggests that it is not a minority of officers that drive the results, but that time-inconsistent output is a widespread practice across the bank's mortgage officers.

4.2. Duration of loan decisions

In examining whether there is also an end-of-month effect in terms of processing duration in reaching a decision over the loan application, we repeat estimation [1], with the dependent variable Y representing the median processing time (in days) at time t for originated loans, denied loans and approved-not-accepted loans, respectively. Also, we omit the three control variables on creditworthiness since they influence the outcome but not the speed of the decision. For originated loans, processing time is defined as the difference between application date and closing date. For denied loans and approved-not-accepted loans, processing time is defined as the difference between application date and the date the decision was taken by the bank.

Table 3 presents the calendar effects on the duration of these decisions. We observe a significantly lesser decision time for originated loan applications that are decided upon on the last working day of the month. Once again, this effect holds solely for loan originations (Columns 3-4), as we find insignificant end-of-month effects for both denied loans and approved/non-accepted loans. In particular, originations that were closed on the last working day of the month have a 2.47 (2.04) days quicker processing time compared to the first day of the month (rest of the month). Moreover, we confirm the gradual nature of the calendar effect. Focusing on originations and plotting the estimated coefficients for each variable in the *Distance* vector from Table 3 (Column 1), Figure 9 demonstrates that the processing time for originated loans becomes

[26] Notably, the same results are found even when we repeat specification [1] separately for each product category (i.e., Fixed, ARM, Balloon, Interest-Only).

significantly shorter only during the last two days of the month, reaching its quickest on the last working day of the month.

Notably, this parsimonious specification with calendar effects and the volume of submitted applications (20-day rolling window) explains a large part of the variation in application's processing time. Also, the negative and statistically significant effect of application volume is consistent with the fact that the number of mortgage officers in the bank's retail lending is relatively stable and they face a monthly hurdle occasionally adjusted by the exogenous demand for loans. In other words, mortgage officers have to speed up their processing time when they have an increased number of submitted applications.

4.3. Underwriting

After confirming the end-of-month effect in terms of the volume and duration of origination, the next step is to assess whether there are systematic differences in the creditworthiness of those mortgage applications closed on the last working day of the month. We obtain probit estimates for the likelihood for approval of loan applications:

$$\text{Prob}(Approved_i = 1) = \Phi\{\alpha_0 + \alpha_1 EndofMonth_i + \gamma \text{Month}_i + \delta \text{Year}_i + \mu \mathbf{X}_i\} \qquad [2]$$

where $\boldsymbol{X}$ denotes a vector of control variables that are found in the literature to influence the underwriting process and are also encountered in the bank's policies and procedures, namely credit score, loan-to-value ratio, debt-to-income ratio, loan amount, jumbo loan indicator, refinance indicator, loan type and subordinate lien. We capture calendar differences in loan creditworthiness by interacting the indicator variable for the last working day of the month with the respective variables for credit score, loan-to-value ratio, and debt-to-income ratio. For better interpretation of any creditworthiness differentials, we utilize the cumulative empirical distribution of these variables.

Table 4 demonstrates that mortgages approved on the last working day of the month have lower credit score, higher loan-to-value ratio and higher debt-to-income

ration. There is a 5% lower credit score across product types, while fixed products have 4% higher loan-to-value ratio and non-fixed products have 3% higher debt-to-income ratio. Focusing on the lower quantile of applications, these marginal effects translate to 13 units lower credit score, 11 percent higher loan-to-value, and 2 percent higher debt-to-income, respectively. From a practical viewpoint, these results verify that mortgage officers exercise some discretion over marginal cases.

4.4. Pricing

Besides approving applications on the margin, it may also be the case that the pricing offered at the end of the month is lower in order to make it more appealing for the borrower to accept the loan. For this reason, we assess whether there is a systematic difference in the pricing of the originated loans closed on the last working day of the month.[27] We obtain OLS estimates for pricing using the following specification for the annual percentage of rate (APR) of the originated loan i:

$$APR_i = \beta_0 + \beta_1 EndofMonth_i + \gamma \text{Month}_i + \delta \text{Year}_i + \kappa \mathbf{Z}_i + u_i \qquad [3]$$

where $\boldsymbol{Z}$ denotes a vector of control variables that are found in the literature to influence the loan pricing process and are encountered in the bank's policies and procedures, namely credit score, loan-to-value ratio, debt-to-income ratio, loan amount, jumbo loan indicator, refinance indicator, loan type, subordinate lien, property type, occupancy indicator, and product type. Preferential pricing at the end of the month would be manifested if $\beta_1 < 0$.

Table 5 presents the results. We find no end-of-month effect in mortgage pricing. At the same time, the control variables have the expected sign. Higher credit score reduces the offered APR, in contrast to higher loan-to-value ratio or debt-to-income ratio. Also, any additional loan amount above the jumbo cutoff has a positive effect on

[27] We focus on originations rather than all approvals since the bank does not consistently keep records for the ARP of approved-not-accepted loans. This does not affect the basic premise of our hypothesis.

the price of the mortgage, while the insurance offered by non-conventional loans (e.g., FHA, VA) reduces the risk premium required for mortgage pricing. These results suggest that although originating some mortgages of marginally lower-quality, the mortgage officers seem to be appropriately pricing these loans for the additional risk. Finally, it is worth mentioning that in underwriting and pricing estimations we incorporate most variables mentioned in the bank's policies for these decisions, as evident from the specifications' high predictive power.

4.5. Loan performance

With loan officers originating some marginal applicants on the last working day of each month, one would expect the loan performance for that cohort of borrowers to be slightly worse. To thoroughly evaluate the effect of time-varying behaviour of mortgage officers on loan performance, we focus on both the likelihood of delinquency as well as the length of time until delinquency, using probit regression and survival analysis, respectively. In order to indicate the predictive power and the robustness of the results under different levels of parsimony, we estimate the following probit regressions:

$$\text{Prob}(Delinquency_i = 1) = \Phi\{\alpha_0 + \alpha_1 EndofMonth_i + \alpha_2 State_i + \gamma SemiAnnual_j\} \qquad [4]$$

$$\text{Prob}(Delinquency_i = 1) = \Phi\{\beta_0 + \beta_1 EndofMonth_i + \delta(\text{Month}_i \cdot \text{Year}_i) + \lambda \mathbf{X}_i\} \qquad [5]$$

where *Delinquency* for mortgage i is an indicator of delinquency at any point through March 2011, *EndofMonth* is an indicator variable denoting loans closed on the last working day of a month, *State* is an indicator variable denoting loans for properties located in the four states with the highest decline in housing prices (namely Arizona, California, Florida and Nevada) in order to reflect particularly adverse local economic conditions, *SemiAnnual* is a vector of dummies indicating the semi-annual origination periods presented in Figure 7, and X is a vector of explanatory variables found in the literature to predict probability of delinquency (see Demyanyk and Van Hemert, 2011; Jiang et al., 2011; Rajan et al., 2008). These include loan characteristics (loan-to-value

ratio, loan amount, FHA-insured indicator, VA-guaranteed indicator, non-owner occupied indicator, interest-only indicator, low/no documentation indicator) and borrower creditworthiness (FICO score, debt-to-income ratio) that reflect the observable risk profile of the applicant at the time of the loan agreement. We also control for the daily number of originated loans in order to account for initial conditions, since the loan origination productivity greatly varies within each month. Overall, we expect the *EndofMonth* indicator to have a positive and significant marginal effect on the likelihood of delinquency.

In terms of survival analysis, we estimate a survival model with cured fraction using the same independent variables from [4] and [5] for consistency purposes. Standard survival models with censoring are not appropriate in the context of loan performance given their implicit assumption that the incident of interest (i.e., delinquency) will eventually happen for the entire loan population, although this is not observable within the existing monitoring period. Instead, a survival model with cure fraction assumes that a substantial part of the loan portfolio will not experience delinquency. We use a parametric mixture cure model that estimates both the proportion of loans unaffected by delinquency from origination due to their high quality, and the conditional survival function for the remaining loans that will experience delinquency (Boag, 1949; Berkson and Gage, 1952; Maller and Zhou, 2001). In this way, the survival distribution function of the survival model is the mixture of the respective function for each sub-population $S(t) = \pi S_{Cured}(t) + (1-\pi)S_{Uncured}(t)$ based on the estimated weight π, which depends on the explanatory variables and reflects the probability of not experiencing delinquency. This can be further simplified to $S(t) = \pi + (1-\pi)S_{Uncured}(t)$, since the limit of $S_{Cured}(t)$ is equal to one as t approaches infinity. We choose the lognormal distribution for the cure model since the majority of the loans in our sample does not experience delinquency (see Appendix A illustrating this asymptotically non-zero probability), and because the hazard in loan delinquencies increases initially, but then rapidly decreases with time (see

Figure 7). We expect that the indicator of end-of-month loans will have a negative and significant effect on the length of time until delinquency.

Table 6 presents the results from the two alternative specifications for each estimation methodology. Consistent with our hypothesis, all estimates for the end-of-month indicator have the expected sign and are highly statistically significant, while the magnitude of these estimates does not vary substantially across the two specifications, despite the plethora of control variables in the augmented specification. Based on the probit regression, we find that mortgages originated on the last working day of the month have 1% higher likelihood for delinquency compared to mortgages originated on the remaining days of the month (Columns 1-2). Although this magnitude might seem small, we should emphasize that mortgage originations on the last working day of each month account for 13.6% of the total number of originated mortgages (and 13.6% of the total loan amount) in the bank's retail channel during the 2006-2008 period.[28] Also, we find the mixture cure model estimates for the end-of-month loans to be negative and highly statistically significant, suggesting that mortgages originated on the last working day of the month become delinquent sooner than the rest of the loans in the month (Columns 3-4). For instance, using the estimates in Column 3, we find that for loans originated in the first half of 2006 for properties in Arizona, California, Florida, or Nevada, the difference in survival functions between end-of-month loans and the remaining loans is 1% after four years and 1.2% after five years.

One could argue that delinquency does not necessarily create substantial cost for the firm since delinquent borrowers may manage to overcome their financial difficulties and become current again in their mortgage obligations. However, it is important to note that similar patterns are found when we consider the likelihood of a foreclosure outcome that undoubtedly imposes substantial costs on the bank. For instance, in a

[28] In comparison, the sum of the last working days of the month is 4.8% of all the working days during the 2006-2008 period.

random sample of 100,000 loans from the OCCMM dataset for the bank's portfolio loans from the retail lending channel, we find that 14.4% of the foreclosures are mortgages originated on the last working day of the month. The respective portion of the end-of-month mortgages in the random sample is 13.5% and the difference between the two proportions is statistically significant at the 1% level, further highlighting the lower performance of these mortgages.[29]

The results for end-of-month originations in terms of underwriting, pricing and loan performance are related to the tiered nature of risk-based pricing, which relies on credit risk buckets (e.g., for credit score and LTV) with approved loans being assigned the same price premium as long they belong within the same risk bucket. Although end-of-month originations are found to be of marginally lower quality, they seem to be appropriately priced because banks typically rely on broad risk groupings for risk-based pricing. In reality, this creditworthiness differential could be reflected on the loan performance. Indeed, conditional on the loan price, we find that the end-of-month loans have different distribution within credit risk buckets, with marginally higher concentration on the lower-end (higher-end) of the credit score (LTV) bucket.[30]

4.6. A closer look at nonlinear incentives and loan performance

The previous section illustrates that the inclusion of some marginally approved applications on the last working day of each month – on average – increases the

[29] We draw a random sample in order to avoid identifying the bank. Nevertheless, this random sample is sufficiently large to provide meaningful comparisons. We opt not to perform a detailed estimation of the likelihood of foreclosure since that would demand a much richer set of explanatory variables in order to accurately reflect the mortgage-specific loss mitigation process that is often affected by state-level regulatory changes.

[30] We created seventeen successive sub-samples of approved loans based on APR (loans with APR between 5.000%-5.249%, 5.250%-5.499%, 5.500%-5.749%, etc., up to 9.249%). This APR range (5.000%-9.249%) captures 98% of the approved loan population, and the 0.250% increments offer sufficient sample size for meaningful analysis. For each sub-sample we then performed a Kolmogorov-Smirnov test for equality of distribution function for the LTV variable across the group of loans that were issued on the last working day of the month and the group of loans that were issued on any other day of the month, except the last working day. In the majority of these sub-samples (11 out of 17) we find the group of end-of-month loans to have different distributions at the 10% level of statistical significance, with marginally higher LTV values. These distributional differences are also confirmed for the credit score variable, where we find that the group of end-of-month loans has marginally lower credit score values (in 14 out of the 17 sub-samples).

likelihood of delinquency and reduces the length of time until delinquency for these loans, originated during the 2006-2008 period. However, the concept of a "marginal approval" varies widely, given the fluctuation of creditworthiness requirements across time. As such, we would expect origination spikes from nonlinear incentives to have an adverse effect on loan performance only during periods in which creditworthiness requirements are less stringent.

Although a thorough empirical investigation of this issue would require longer time periods, it would be useful to provide an insight and possibly qualify the results in Section 4.5 by plotting performance estimates for end-of-month loans against creditworthiness characteristics of all originations over quarterly periods. Figure 10 offers correlations between three applicant characteristics, namely FICO score, debt-to-income ratio and income, and the quarterly estimates from probit regression.[31] Given the prevalence of risk-based pricing, we also include the 90th percentile for APR as a proxy for applicant riskiness across quarters.

The quarterly results refine the results across the entire 2006-2008 period, as shown in Section 4.5. In particular, we observe that the negative and statistically significant relationship between end-of-month loans and loan performance holds only for three quarters out of twelve. As expected, compared to the other quarters during the 2006-2008 period, originations in these three quarters consistently have below-average FICO scores and above-average debt-to-income scores, as well as longer left (right) tail for income (APR). Also, compared to the overall estimate for the 2006-2008 period, the magnitude of the estimates is considerably larger for these three quarters. In particular, the end-of-month loans originated in these quarters are expected to have about 3-4% higher delinquency likelihood compared to loans originated during the remainder of the month. Finally, from a comparative perspective, our finding implies that across lenders

[31] Other measures (e.g., loan-to-value ratio) are not used in Figure 10 because they have little fluctuation across time.

using nonlinear incentives for their mortgage officers, those lenders with lower underwriting standards will experience a greater negative effect on the performance of end-of-month loans.

5. Borrower preferences as an alternative explanation

Even though using the daily variation in mortgage activity for a single bank does not establish an indisputable causal link between nonlinear incentives and time-varying output, alternative factors cannot fully explain the stylized facts outlined above. One alternative factor could be applicants' preferences. In particular, applicants may proactively select the closing date to coincide with the end of the month, either *directly* by timing the submission of their application, or *indirectly* by requesting the loan officer and other related parties to delay the closing date until the last day of the month. However, while these scenarios might seem plausible, they cannot explain our findings for several reasons.

First, if fluctuations were affected by borrower preferences then we would expect all lenders to experience end-of-month spikes in origination volume. However, this is not the case. Using the publicly available HMDA data for 2009 originations, and focusing on lenders with at least 8,000 originations, we find that only a third of the lenders (12 out of 35) exhibit these end-of-month spikes.[32]

Second, if borrowers request their closing date to be on, or closer to, the last working day of the month, then we would observe a bimodal distribution in processing time since applications would be either rushed to be completed within the same month that they were submitted, or postponed until the end of the subsequent month.[33] Rather, we observe a unimodal distribution in processing time of originated mortgage

[32] Although the publicly available HMDA does not offer information on the channel (retail/broker/ correspondent), we can safely assume that the effect mostly reflects retail activity since any wholesale activity was substantially reduced during 2009 as a result of the financial crisis.

[33] As a result, the distance between the two peaks would be approximately thirty days.

applications, regardless of how we group the applications based on their time of submission (see Appendices B and C). In a related fashion, submission timing is not meaningful since there is a wide variation in processing time of mortgage applications. This is contrary to commercial activities such as car sales, where salesmen often have monthly quotas and processing time is minimal. In this sense, customers could opt to make the purchase on the last day of the month in order to obtain better terms.

Third, even though borrowers' preferences (or even sellers' preferences) might play some role in the closing time of home purchases due to the timing of transition between properties, this is not the case for refinances, whose timing is generally lender-driven. Also, given the per diem interest, closing at the end of the month does not offer any financial benefit for the borrower, with the exception of refinancing applications when the last working day of the month is not a Friday. More specifically, when a borrower refinances an existing mortgage, it is better to avoid closing on a Friday because it will increase the number of days of interest pay on both loans by 2-3 days. However, in our sample we find no substantial difference in mortgage closings across weekdays, with 19.16% of refinances being closed on Fridays.[34] Additionally, the booming housing market in 2006-2007 (during which properties remained on the market only for a short time period) did not allow strategic timing for mortgage closing dates in home purchases. Notably, our results are robust in terms of magnitude and statistical significance even if we perform the estimations separately for home purchases and refinances.

Fourth, once the mortgage application gets the clear to close, mortgage officers could effectively influence the final settlement date for a property since they typically coordinate that date with the prospective buyer, the title/escrow company and other

[34] The distribution of closing days for refinances in our sample is as follows: Monday 22.31%, Tuesday: 20.83%, Wednesday: 23.5%, Thursday: 14.20%, and Friday: 19.16%. Also, the percentage for Friday closing for refinances is relatively stable across years (19.54% in 2006, 20.52% in 2007 and 18.62% in 2008).

related parties. Also, borrowers generally use the lender's (or the real estate agent's) preferred escrow company, while mortgage officers and real estate agents often have ongoing relations, since the latter have an incentive to refer applicants to the former.

Finally, the presence of borrower preferences for choosing a closing date at the end of the month could account for the patterns in origination volume, but not for our findings on the likelihood for approval (Table 4) and the likelihood for delinquency (Table 6).

6. Conclusion

This paper reveals time-inconsistencies in the output of mortgage officers facing a minimum output quota every month. The results are largely in line with agency theory predictions. We find that on the last working day of the month mortgage officers markedly increase their aggregate output by reducing their processing time and approving more marginal applicants. Also, in terms of firm costs, mortgages originated at the end of the month have a slightly higher likelihood for delinquency during periods of relatively lower underwriting standards. Our findings are robust across geographies, indicating that mortgage officers' behavior was not influenced by local housing market conditions or branch management.[35]

Overall, our findings illustrate how a nonlinear incentive design for lower level employees could affect their actions in a manner that can be privately beneficial, but potentially at the cost of organizational efficiency, given the periodic origination of some marginally lower-quality mortgages. In this sense, by demonstrating adverse firm effects in terms of loan performance, we provide evidence for Baker's (2000: p. 417) assertion that the timing of performance measurement for loan officers encourages short-term results, at the expense of long-term results. This is also consistent with Holmstrom and

[35] For robustness purposes, we confirmed our results by repeating estimations [1] through [5] by state or metropolitan statistical area (MSA), excluding those geographies with insufficient sample size.

Milgrom's (1987: p. 325) prediction that if agents are equally effective in allocating time between reducing costs or increasing revenues, while the revenues are subject to more exogenous variance than the costs, then their incentive scheme should also be based on both profits and cost reductions. Although the financial literature typically focuses on the incentives of top executives and their effect on firm performance, this paper acts as a reminder of the important role of the incentive design throughout the organizational hierarchy.

While the focus of the paper is a single bank, our findings have wider policy implications, especially given anecdotal evidence suggesting the use of nonlinear incentives across many banks. Future research could improve causal inference by exploiting variation across banks (or, alternatively, changes within a bank) in terms of mortgage officers' incentive design, productivity patterns and lenders' underwriting standards. In case our findings are replicated for several other banks, one may want to consider the systemic consequences due to the substantial amount of marginally lower quality mortgages originated towards the end of each month. Finally, it would be important to explore whether the marginally higher probability of delinquency for end-of-month loans is already taken into account in the secondary mortgage market, or whether originating banks may potentially benefit from this private information.

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Figure 1: Daily volume of mortgage decisions

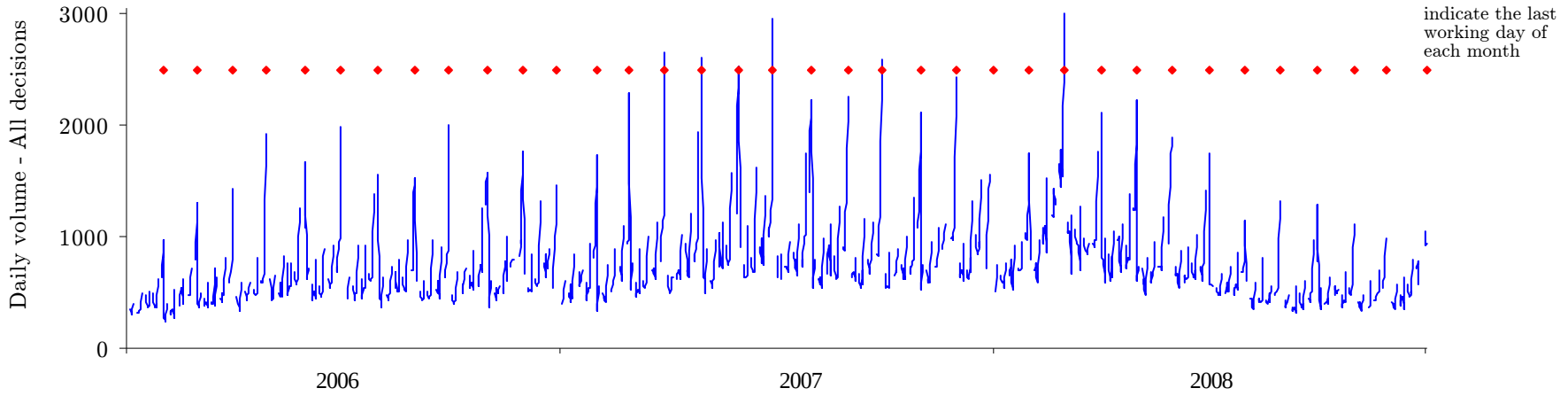


Figure 2: Daily volume of originations

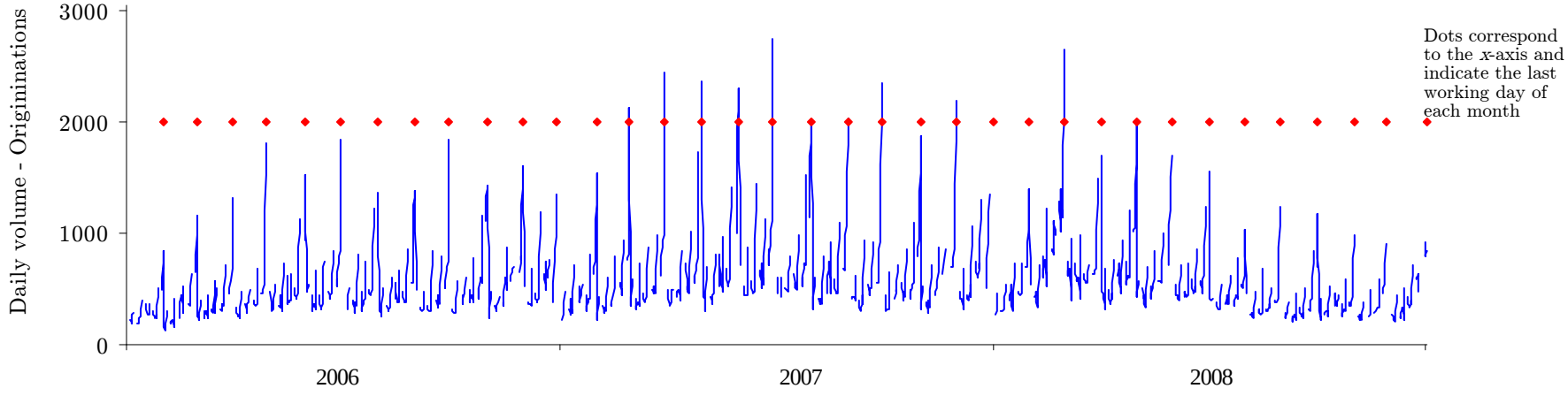


Figure 3: Daily volume of denied mortgage applications

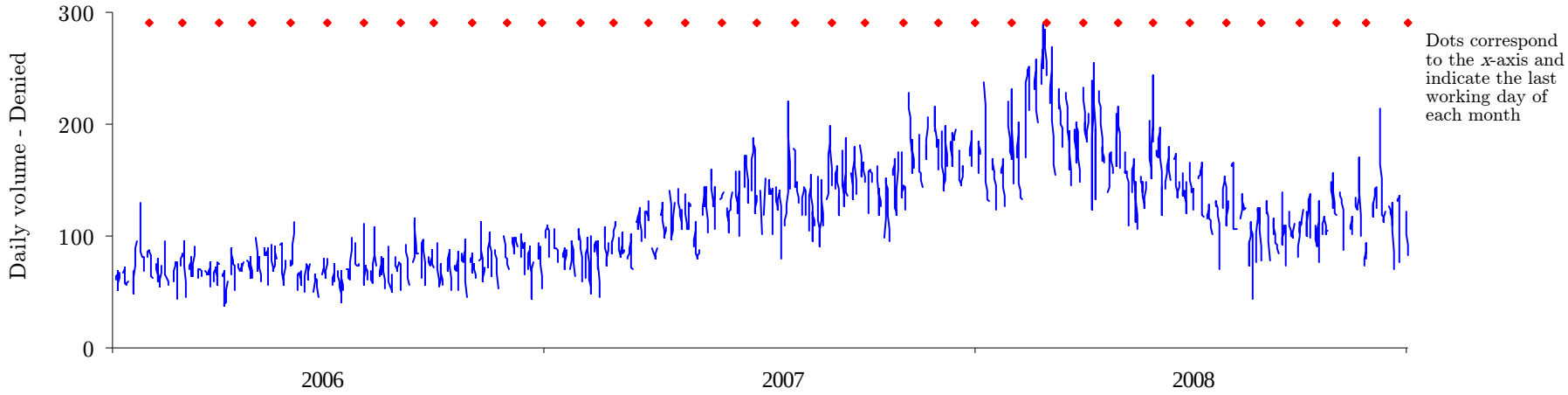


Figure 4: Daily volume of approved, but not accepted, mortgage applications

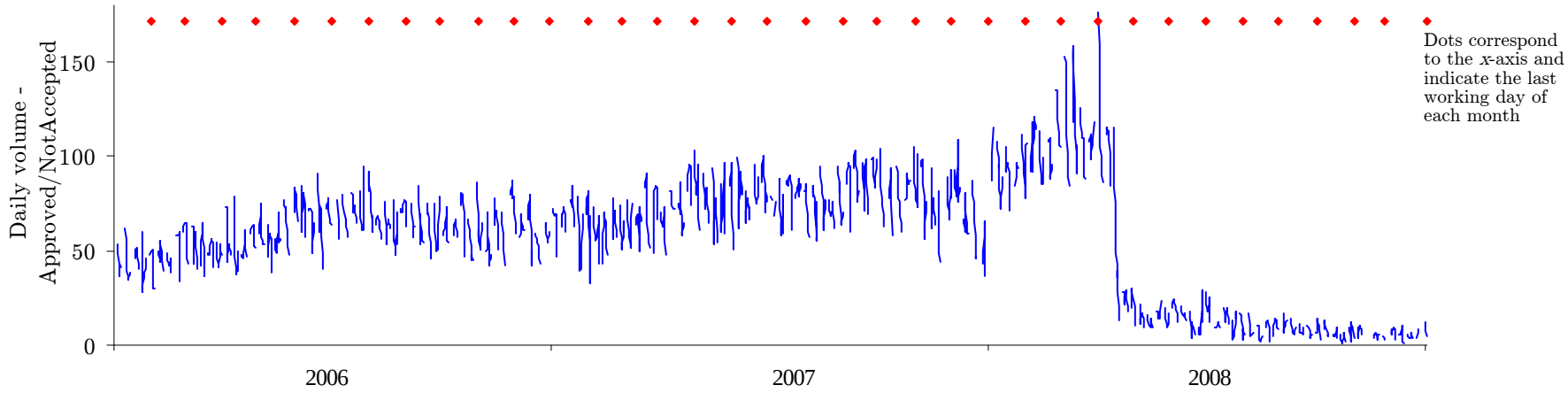


Figure 5: Daily volume of submitted mortgage application

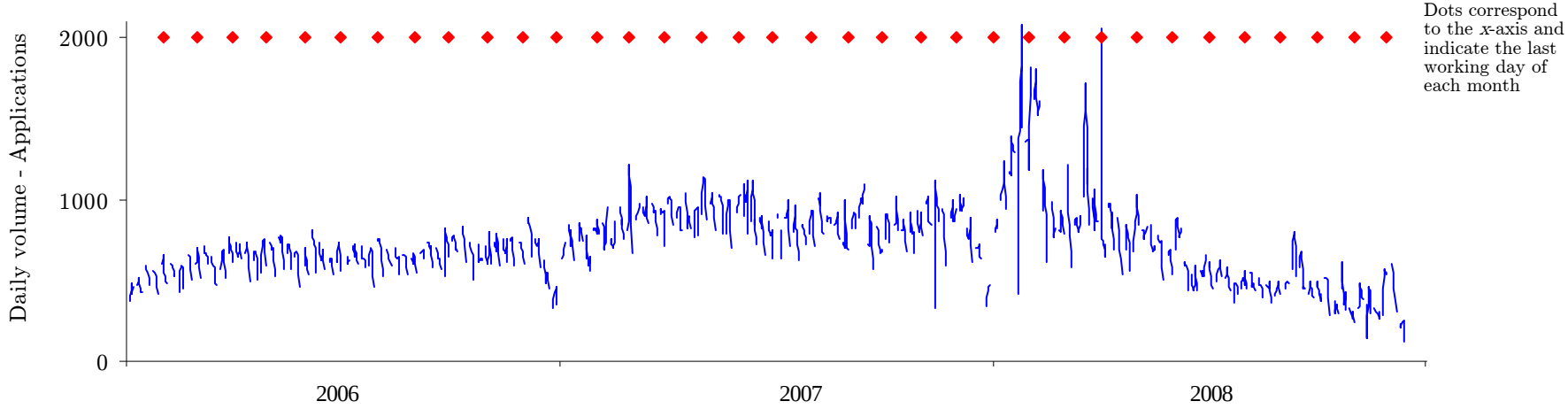


Figure 6: Daily average loan amount of approved applications

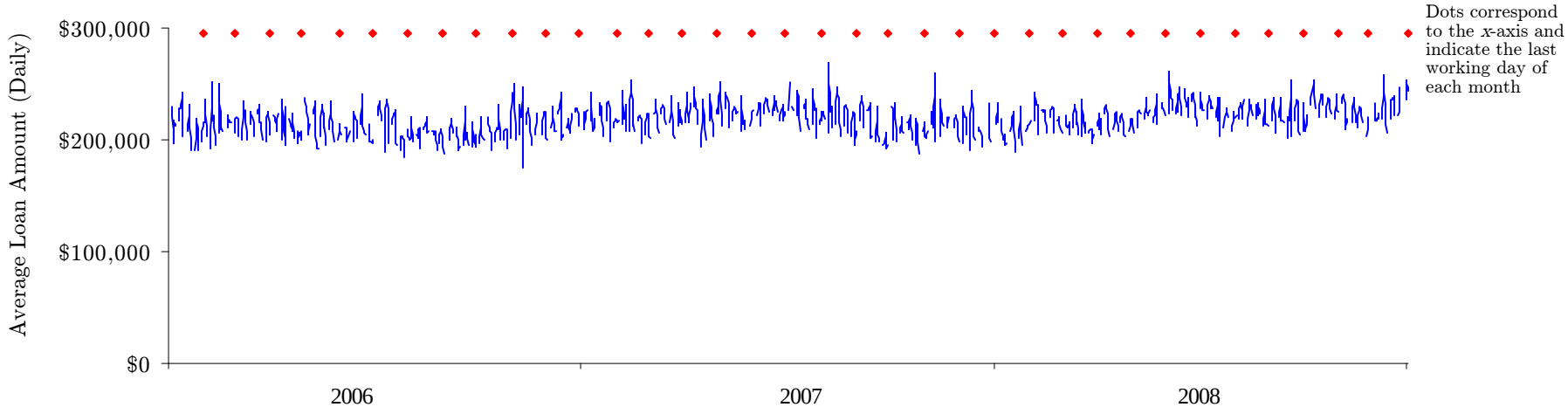


Figure 7. Cumulative delinquency rates since loan origination (by Semi-Year)

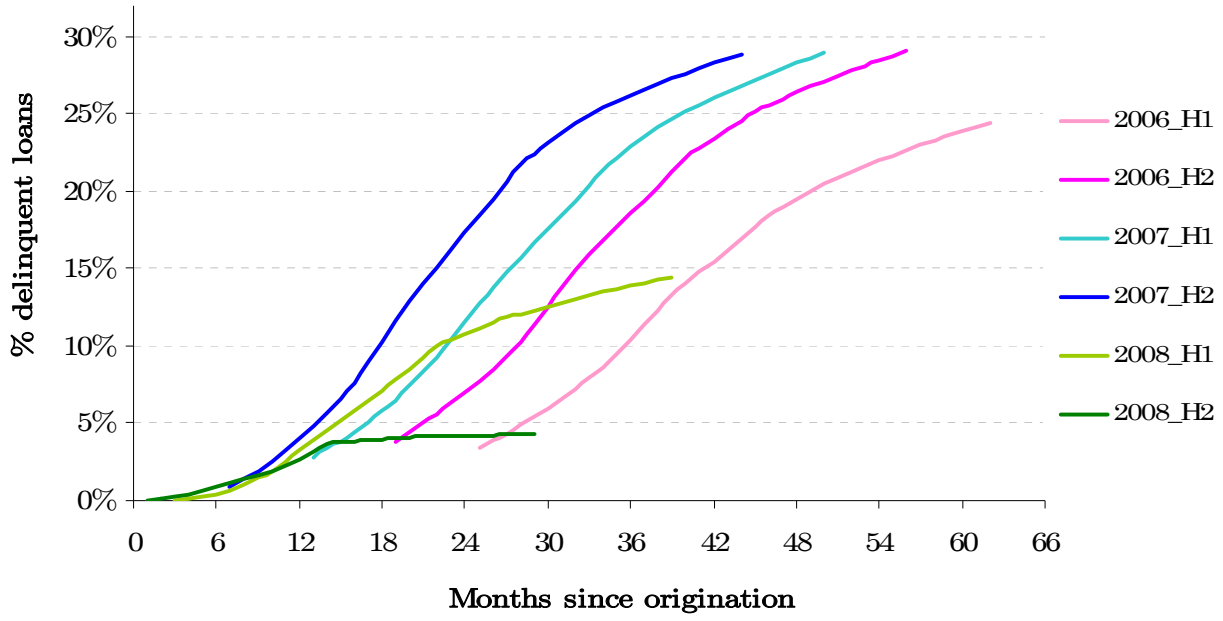
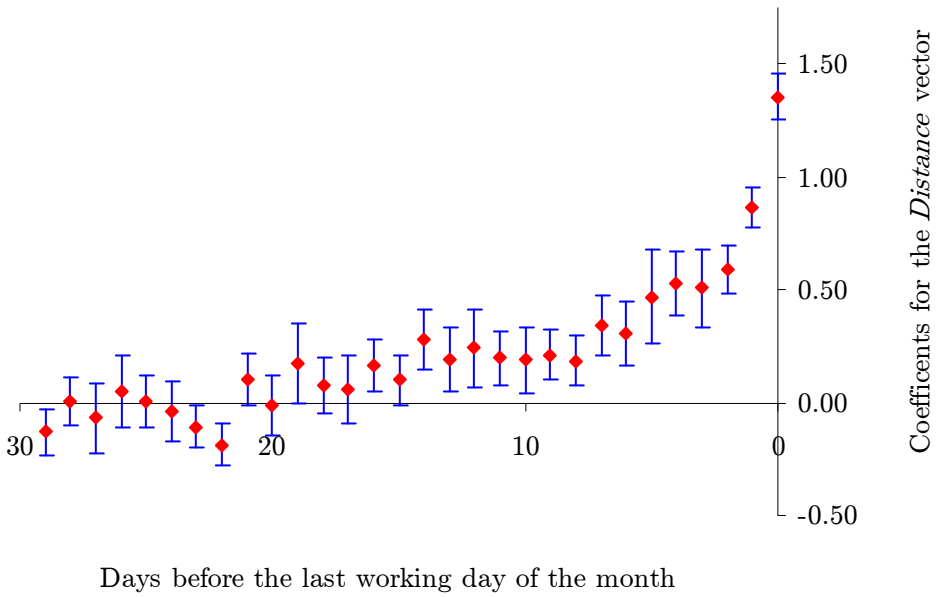
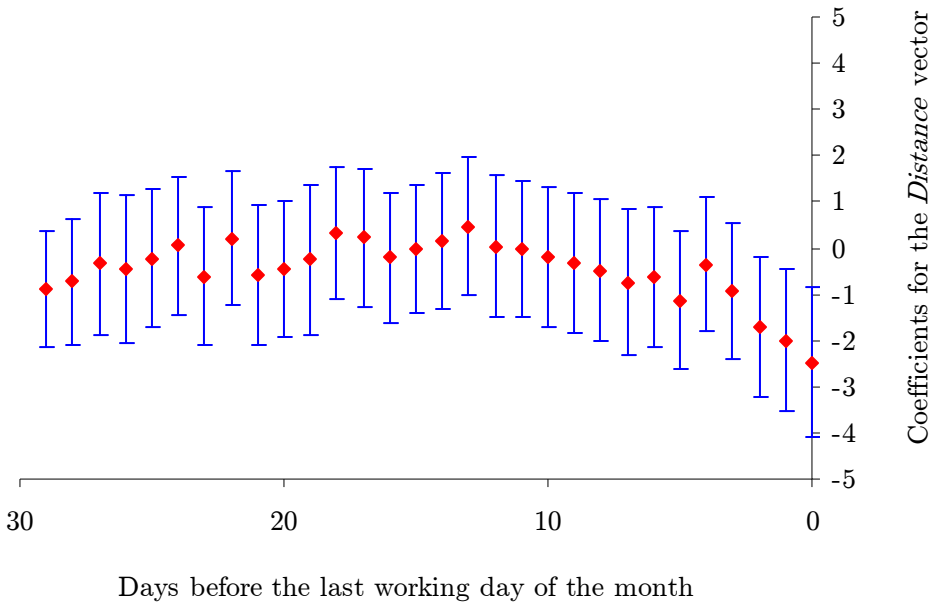


Figure 8: Effect on Output over the Monthly Cycle



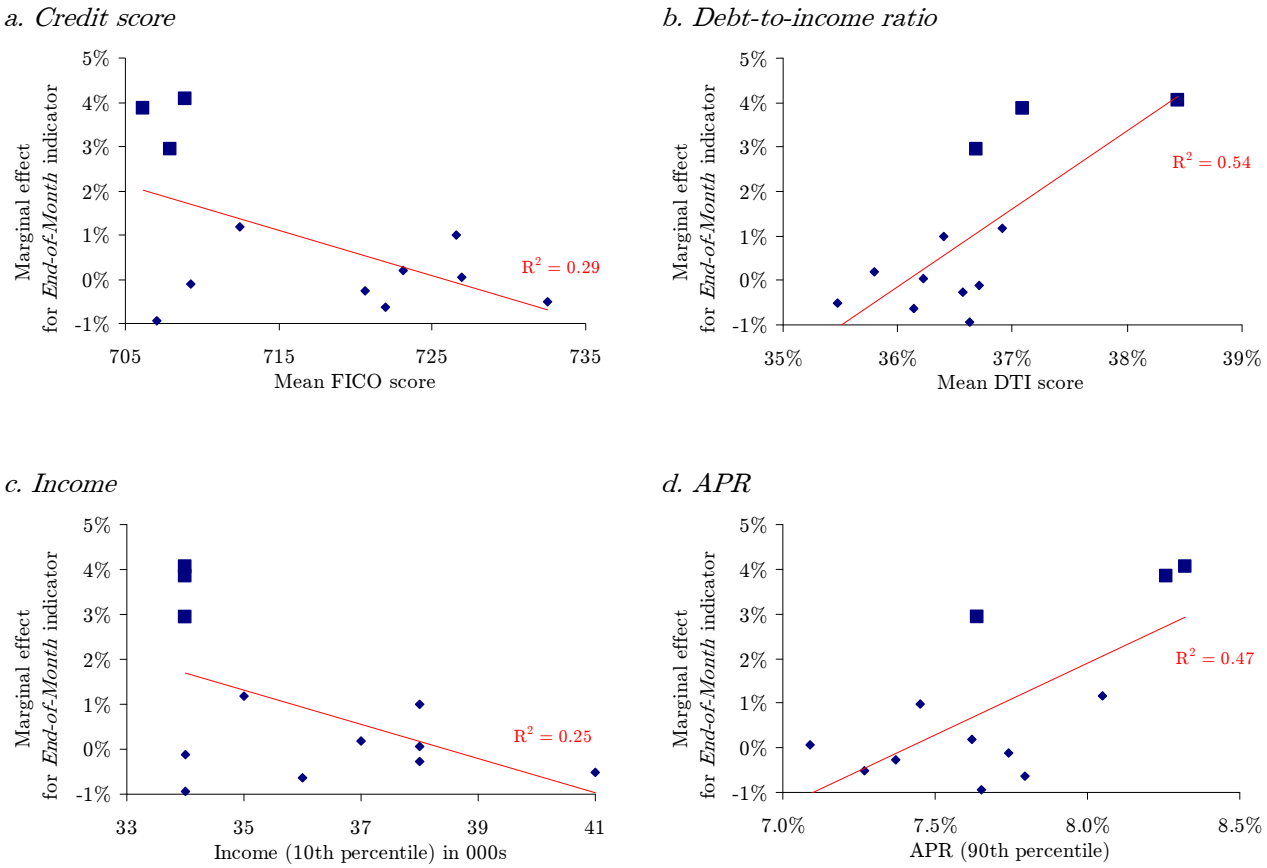
NOTE: The solid line presents the estimated coefficients for the *Distance* vector in specification [1] as presented in Table 2 (Column 1), while the bars are the 95% confidence intervals for the point estimates.

Figure 9: Effect on Processing Time over the Monthly Cycle



NOTE: The solid line presents the estimated coefficients for the *Distance* vector in specification [1] as presented in Table 3 (Column 1), while the bars are the 95% confidence intervals for the point estimates.

Figure 10: End-of-month loans, loan performance and loan characteristics across quarters



NOTE: Each point reflects a quarter during the 2006-2008 period. The vertical axis presents probit estimates (marginal effects) for the *End-of-Month* indicator, separately for each quarter. All estimations reflect specification [5], as outlined in Table 6, Column 2. Squares denote an estimate that is statistically significant at the 5% level. The pseudo-R^2 for the twelve estimations ranges between 11.3% and 22.4%.

Table 1
Sample Overview: Loan Characteristics

Columns 1-4 provide descriptive statistics for the HMDA Plus sample used in the estimations. This sample contains 578,233 loan applications for a bank (retail lending) during the period Jan. 2006-Dec. 2008. These loan applications had one of the following outcomes: originated, approved/not-accepted, or denied. Column 5 presents descriptive statistics for a sub-sample of 388,300 originations for which we have loan performance information after merging the bank's retail HMDA Plus data with the OCC Mortgage Metrics dataset. The asterisk (*) illustrates omitted dummies in the specifications, while (0/1) indicates a dummy variable.

	All loan applications	*Originated applications*	*Denied applications*	*Approved/ Not Accepted applications*	*Matched originations*
Loan Characteristics	[1]	[2]	[3]	[4]	[5]
a. Loan type (0/1)					
▪ Conventional *	0.89	0.89	0.82	0.96	0.89
▪ FHA-insured	0.09	0.09	0.16	0.03	0.09
▪ VA-guaranteed	0.02	0.02	0.02	0.01	0.02
b. Loan purpose (0/1)					
▪ Home purchase *	0.74	0.77	0.59	0.72	0.76
▪ Refinancing	0.26	0.23	0.41	0.28	0.24
c. Occupancy (0/1)					
▪ Owner-occupied *	0.86	0.87	0.85	0.83	0.88
▪ Not owner-occupied	0.14	0.13	0.15	0.17	0.12
d. Property type (0/1)					
▪ 1- to 4-family dwelling *	0.98	0.98	0.97	0.99	0.98
▪ Manufactured housing	0.02	0.02	0.03	0.01	0.02
e. Product type (0/1)					
▪ Fixed	0.75	0.77	0.73	0.64	0.78
▪ ARM	0.05	0.05	0.05	0.07	0.04
▪ Balloon	0.12	0.11	0.13	0.18	0.11
▪ Interest Only	0.06	0.05	0.06	0.07	0.05
▪ Other	0.02	0.02	0.03	0.04	0.02
f. Lien status (0/1)					
▪ Secured by a first lien *	0.87	0.88	0.86	0.80	0.88
▪ Secured by a $2^{nd}/3^{rd}$ lien	0.13	0.12	0.14	0.20	0.12
g. Loan amount	$217,848	$213,628	$230,883	$234,308	$215,811
h. Debt-to-income ratio (DTI)	37.78%	36.40%	46.16%	34.76%	36.64%
i. Loan-to-value ratio (LTV)	72.87%	72.69%	77.74%	64.79%	73.33%
j. Credit score (i.e., FICO score)	712.38	717.66	680.28	723.93	716.20
k. End-of-Month closing dates	11.65%	13.60%	5.10%	5.08%	13.55%
l. Other characteristics					
▪ Daily volume (mean)	756	583	116	57	
▪ Daily volume (median)	661	481	109	61	
▪ Days to process (mean)	36	35	33	42	
▪ Days to process (median)	29	29	24	32	
Observations	568,027	437,645	87,408	42,974	388,300

Table 2
End-of-Month Effect on the Number of Loan Decisions

Each column represents an OLS regression. The dependent variable interchangeably denotes the daily number of originated applications (Columns 1-2), denied applications (Columns 3-4) and approved-not-accepted applications (Columns 5-6), respectively, at time *t*. All dependent variables are in natural logarithm form. Application volume denotes the number of submitted applications between time *t* and *t-19*, thus capturing possible variation in the aggregate workload. The mean Credit Score, mean Loan-to-Value ratio (LTV), and mean Debt-to-Income ratio (DTI) of submitted applications between time *t* and *t-19*, reflect variations in the application quality across time. The values of Newey-West errors (with six lags) appear in parentheses below each coefficient estimate. Standard errors using the Newey-West method are based on consistent estimates of the covariance matrix in the presence of both heteroskedasticity and autocorrelation. The 'End-of-Month' indicator denotes the last working day of the month, and along with the 'Day effects' consist the *Distance* vector in specification [1]. The Wald test is used to test for equality of the estimates for the *Distance* vector. A constant term is included, but not reported. Asterisks denote significance at 1 percent (**) and 5 percent (*) levels.

	Number of Originated Loans (ln)		*Number of Denied Loans (ln)*		*Number of Approved/Not-Accepted loans (ln)*	
Independent Variables	[1]	[2]	[3]	[4]	[5]	[6]
End-of-Month indicator	1.388**	1.204**	0.058	0.074*	-0.304**	0.050
	(0.052)	(0.036)	(0.068)	(0.035)	(0.103)	(0.050)
Application volume over 20 days (*ln*)	0.247**	0.208	0.158**	0.136**	0.218**	0.191**
	(0.055)	(0.114)	(0.039)	(0.037)	(0.052)	(0.051)
Credit Score *(20-day mean)*	-0.019**	-0.020**	-0.006	-0.007*	-0.071**	-0.072**
	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)
LTV *(20-day mean)*	-0.032*	-0.031**	-0.039**	-0.040**	-0.162**	-0.164**
	(0.005)	(0.010)	(0.005)	(0.004)	(0.008)	(0.008)
DTI *(20-day mean)*	-0.135**	-0.124**	0.010	0.007	-0.322**	-0.328**
	(0.021)	(0.044)	(0.019)	(0.019)	(0.037)	(0.038)
Day effects	Yes	No	Yes	No	Yes	No
Month effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	751	751	751	751	750	750
R^2	0.742	0.483	0.731	0.714	0.884	0.877
Wald test (F-value)	105.40**	—	1.57*	—	0.98	—

Table 3
End-of-Month Effect on Median Duration (in days) of Loan Decisions

Each column represents an OLS regression. The dependent variable reflects the median decision duration (in days) for originated applications (Columns 1-2), denied applications (Columns 3-4) and approved-not-accepted applications (Columns 5-6), respectively, at time *t*. Application volume denotes the number of submitted applications between time *t* and *t-19*. The values of Newey-West errors (with six lags) appear in parentheses below each coefficient estimate. Standard errors using the Newey-West method are based on consistent estimates of the covariance matrix in the presence of both heteroskedasticity and autocorrelation. The 'End-of-Month' indicator denotes the last working day of the month, and along with the 'Day effects' consist the *Distance* vector in specification [1]. The Wald test is used to test for equality of the estimates for the *Distance* vector. A constant term is included, but not reported. Asterisks denote significance at 1 percent (**) and 5 percent (*) levels.

	Originated Loans		*Denied Loans*		*Approved/Not-Accepted Loans*	
Independent Variables	[1]	[2]	[3]	[4]	[5]	[6]
End-of-Month indicator	-2.469**	-2.041**	-3.221	-0.152	-8.416	-2.130
	(0.818)	(0.310)	(2.207)	(0.898)	(4.313)	(1.655)
Application volume over 20 days (*ln*)	-3.217**	-3.033**	-3.307*	-3.432*	-12.062**	-12.016**
	(0.954)	(0.994)	(1.562)	(1.576)	(4.224)	(4.097)
Day effects	Yes	No	Yes	No	Yes	No
Month effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	751	751	751	751	750	750
R^2	0.518	0.473	0.418	0.391	0.491	0.474
Wald test (F-value)	3.31**	—	1.24	—	0.95	—

Table 4
End-of-Month Effect on Likelihood for Approval

Each column presents a probit regression. The dependent variable is the binary outcome (1=Accept, 0=Reject) of a mortgage application. The 'End-of-Month' indicator denotes the last working day of the month, effectively comparing that day with the remaining working days of the month. The remaining control variables are related to the underwriting policy and are described in Table 1. The values of robust standard errors (with product-code clustering) appear in parentheses below each coefficient estimate. A constant term is included, but not reported. *Non-Fixed Products* refers to products that are either *ARM* (27,339 obs.), *InterestOnly* (31,523 obs.), *Balloon* (67,277 obs.), and other various minor types (13,403 obs.). Asterisks denote significance at 1 percent (**) and 5 percent (*) levels.

	All products	*Fixed products*	*NonFixed products*
Independent Variables	[1]	[2]	[3]
End-of-Month indicator (EoM)	0.083**	0.074**	0.088**
	(0.004)	(0.005)	(0.009)
cdf(Credit score)	0.196**	0.189**	0.243**
	(0.013)	(0.011)	(0.033)
cdf(Credit score) × (EoM=1)	-0.053**	-0.053**	-0.031*
	(0.006)	(0.006)	(0.014)
cdf(LTV)	-0.217**	-0.205**	-0.366**
	(0.070)	(0.077)	(0.066)
cdf(LTV) × (EoM=1)	0.026**	0.044**	-0.007
	(0.007)	(0.009)	(0.010)
cdf(DTI)	-0.117**	-0.126**	-0.102**
	(0.010)	(0.007)	(0.026)
cdf(DTI) × (EoM=1)	0.015*	0.010	0.033*
	(0.006)	(0.006)	(0.014)
Jumbo loan (0/1)	0.164**	0.162**	0.107
	(0.017)	(0.014)	(0.066)
Loan amount (ln)	0.002	0.013**	-0.011
	(0.006)	(0.005)	(0.008)
Jumbo loan × Loan amount	-0.070**	-0.084**	-0.030
	(0.016)	(0.016)	(0.017)
Refinance purpose (0/1)	-0.153**	-0.147**	-0.173**
	(0.011)	(0.015)	(0.009)
FHA-insured loan (0/1)	0.011	0.010	0.063**
	(0.021)	(0.023)	(0.021)
VA-guaranteed loan (0/1)	0.058**	0.054**	0.099**
	(0.018)	(0.020)	(0.017)
Second lien (0/1)	-0.189**	-0.194**	-0.193**
	(0.043)	(0.059)	(0.026)
Month effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	568,027	428,485	139,542
Pseudo- R^2	0.131	0.138	0.128

Table 5
End-of-Month Effect on Pricing of Originated Loans

Each column represents an OLS regression. The dependent variable is the Annual Percentage Rate (APR) of approved and accepted loan applications (i.e., originated mortgages). The 'End-of-Month' indicator denotes the last working day of the month, effectively comparing that day with the remaining working days of the month. The remaining control variables are related to the pricing policy and are described in Table 1. The values of robust standard errors appear in parentheses below each coefficient estimate. A constant term is included, but not reported. *Non-Fixed Products* refers to products that are either *ARM* (19,638 obs.), *InterestOnly* (23,461 obs.), *Balloon* (48,559 obs.), and other various minor types (9,165 obs.). Asterisks denote significance at 1 percent (**) and 5 percent (*) levels.

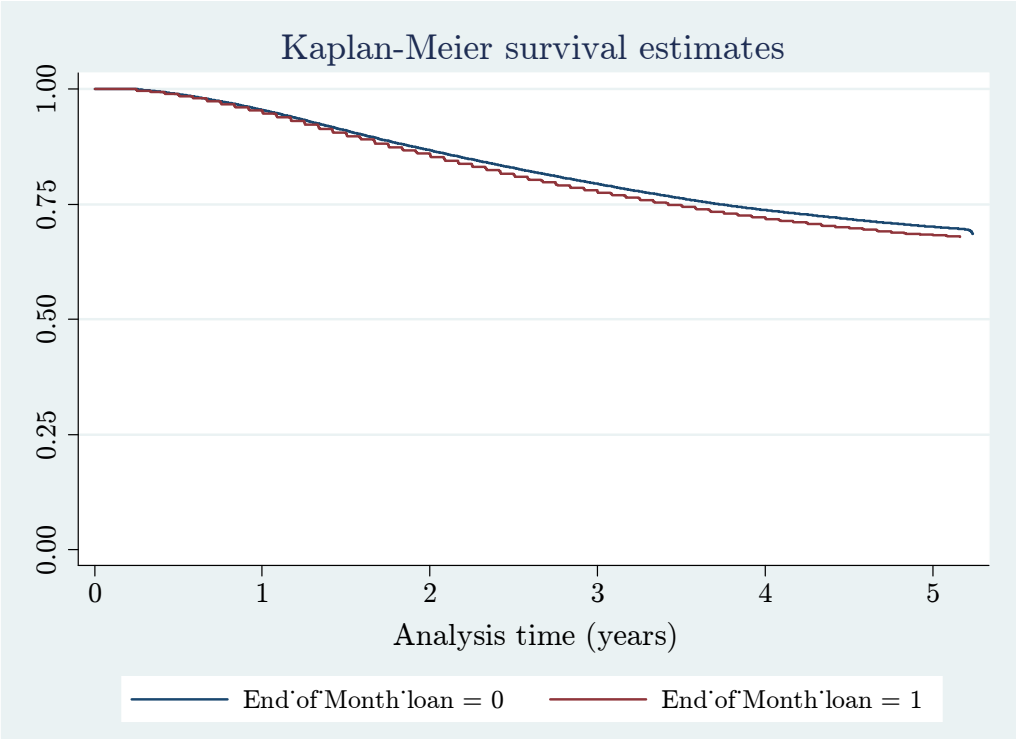
	All products	*Fixed products*	*NonFixed products*
Independent Variables	[1]	[2]	[3]
End-of-Month indicator	0.003	0.001	-0.002
	(0.004)	(0.004)	(0.012)
Credit score	-0.001**	-0.001**	-0.002**
	(0.000)	(0.000)	(0.000)
LTV	0.007**	0.006**	0.009**
	(0.001)	(0.001)	(0.002)
DTI	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.001)
Jumbo loan (0/1)	-1.545**	-1.570**	-1.141**
	(0.330)	(0.372)	(0.342)
Loan amount (ln)	-0.252**	-0.267**	-0.187**
	(0.031)	(0.038)	(0.029)
Jumbo loan × Loan amount	0.261**	0.269**	0.185**
	(0.057)	(0.066)	(0.058)
Refinance purpose (0/1)	0.015	0.058**	-0.059
	(0.028)	(0.018)	(0.056)
FHA-insured loan (0/1)	-1.148**	-0.919**	-0.312*
	(0.083)	(0.042)	(0.128)
VA-guaranteed loan (0/1)	-0.684**	0.683**	-1.165**
	(0.100)	(0.022)	(0.197)
Second lien (0/1)	0.420	-0.297**	1.344**
	(0.543)	(0.061)	(0.034)
Manufactured Housing	0.028	0.049**	-0.204**
	(0.024)	(0.019)	(0.030)
Non-owner occupied	0.267**	0.332**	0.062
	(0.069)	(0.059)	(0.042)
Product code effects	Yes	Yes	Yes
Month effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	437,645	336,822	100,823
R^2	0.738	0.594	0.777

Table 6
End-of-Month Effect and Loan Performance

This table presents an assessment of whether loans originated on the last working day of the month have a higher likelihood of becoming delinquent, and whether they become delinquent sooner than loans originated in the remaining days of the month. For the former, we report marginal effects from a probit regression with robust errors (Columns 1-2), while for the latter we employ a parametric mixed cure model using a lognormal distribution and a logistic link function (Columns 3-4). For probit estimation, the dependent variable reflects the binary outcome (1=Delinquent, 0=Current) of a mortgage's performance as of March 2011. For survival analysis, the dependent variable reflects time to delinquency (in years). The 'End-of-Month' indicator denotes the last working day of the month. By "Additional Controls" we mean the inclusion of the following time-invariant variables: credit score, loan-to-value ratio, debt-to-income ratio, loan amount (ln), non-owner occupied indicator, interest-only indicator, low/no documentation indicator, daily origination volume (ln), FHA-insured loan indicator, VA-guaranteed loan indicator, second lien indicator. Also, "Year/Month effects" reflect multiplicative interactions. A constant term is included, but not reported. The entire sample from the HMDA-OCCMM merge for 2006-2008 contains 388,300 unique loan observations, out of which 89,617 loans became 60+ days past due (or worse) at any given point until March 2011, while 298,683 loans were continuously current from their origination until March 2011. In order to simplify the analysis, we group together current loans and loans that were fully prepaid, due to refinance or property sale. The mixture cure model uses a smaller sample because it excludes 6,911 loans that became delinquent before the start of OCCMM's monitoring period (i.e., January 2008). Asterisks denote significance at 1 percent (**) and 5 percent (*) levels.

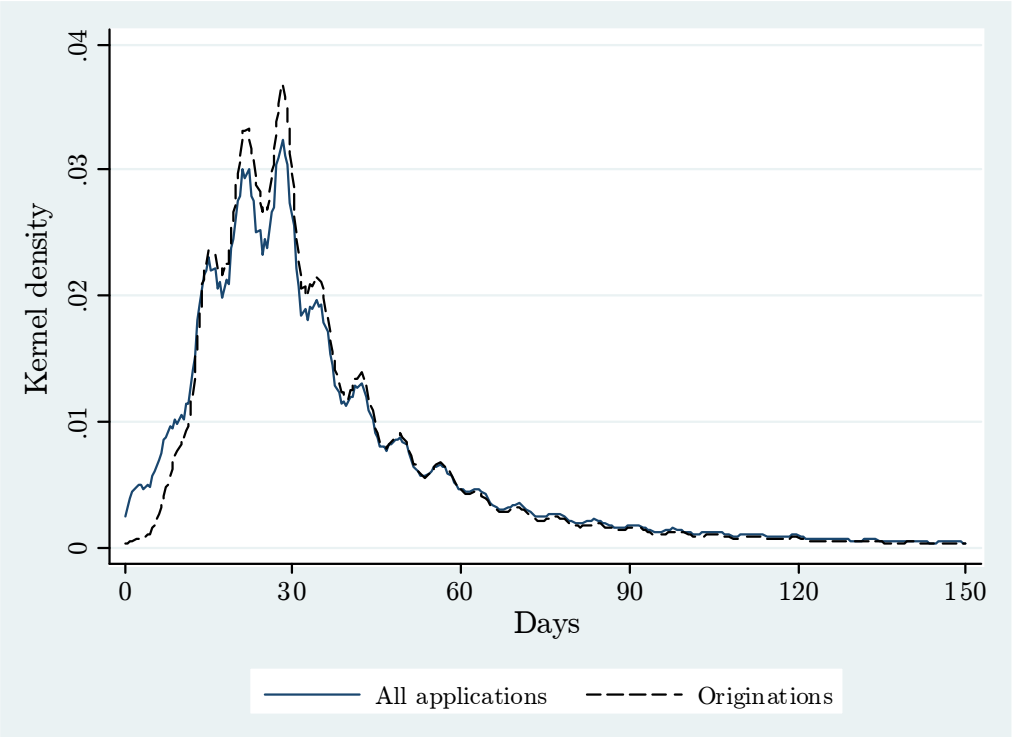
	Probit		Mixture Cure model	
Independent Variables	[1]	[2]	[3]	[4]
End-of-Month indicator	0.011**	0.011**	-0.066**	-0.081**
	(0.002)	(0.003)	(0.015)	(0.025)
Property is located in one of these States: AZ,CA,FL,NV	0.142**	0.175**	-1.046**	-1.463**
	(0.002)	(0.002)	(0.012)	(0.014)
Semi-annual effects	Yes	No	Yes	No
Additional controls:	No	Yes	No	Yes
Year/Month effects	No	Yes	No	Yes
Observations	388,300	388,300	381,389	381,389
Pseudo- R^2	0.066	0.224	–	–

Appendix A: Survivor functions



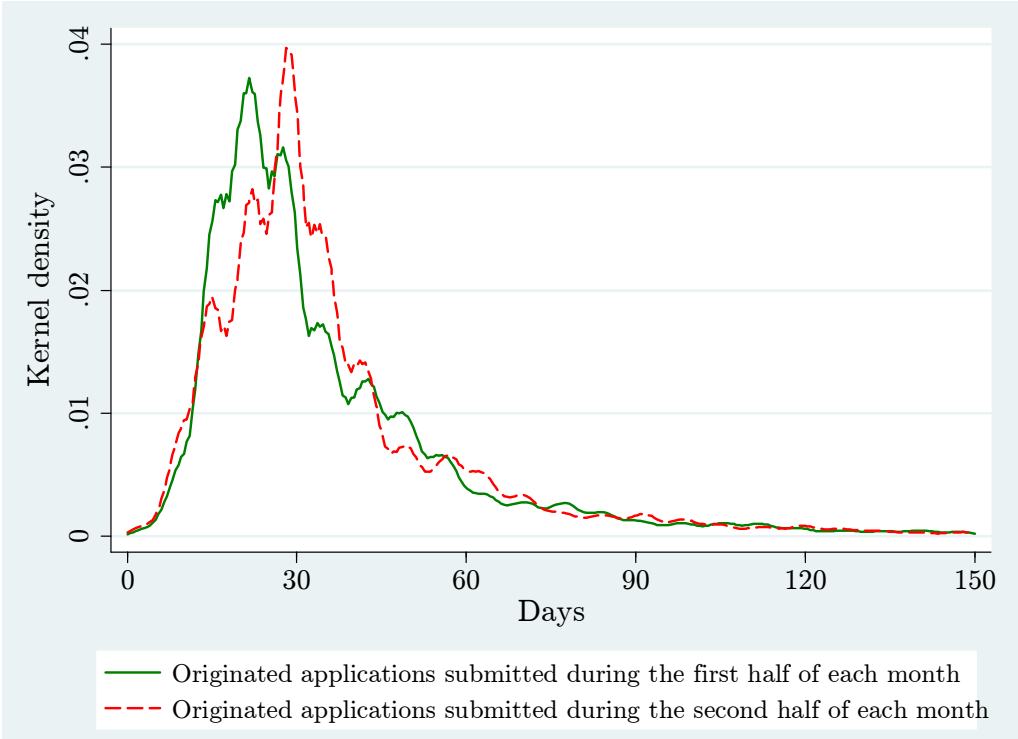
NOTE: The figure illustrates unadjusted Kaplan-Meier survivor functions separately for 52,633 loans originated on the last working day of the month and 335,667 loans originated on the remainder of the month. These 388,300 loans were originated during the 2006-2008 period and their performance reflects information through March 2011. The event of interest is "60+ days past due" delinquency (or worse outcome, such as foreclosure, deed-in-lieu of foreclosure and short-sale). The difference between the two survivor functions is statistically significant at the 1% level.

Appendix B: Distribution of Processing Time



NOTE: The figure illustrates the kernel density distributions for the processing time for 578,233 loan applications (regardless of outcome) and 437,645 originations, respectively, during the 2006-2008 period. For originated loans, processing time is defined as the difference between application date and closing date. For denied loans and approved-not-accepted loans, processing time is defined as the difference between application date and the date the decision was taken by the bank.

Appendix C: Distribution of Processing Time



NOTE: The figure illustrates the kernel density distributions for the processing time for 437,645 originations, during the 2006-2008 period. During the first (1-15) and second (16-31) half of each month there were 224,391 and 213,254 submitted applications, respectively. Processing time is defined as the difference between application date and closing date.