In the Mood for a Loan:

The Causal Effect of Sentiment on Credit Origination

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January 2013

Abstract

We study how loan officers' sentiment affects their decisions on mortgage applications. Motivated by psychological evidence, we use three sentiment proxies: (1) outcomes of key sporting events such as the Super Bowl, (2) outcomes of the American Idol competition, and (3) days around major holidays. Our identification exploits variation in daily loan approvals in each county, while controlling for the volume and quality of reviewed applications. Positive sentiment events are associated with a 4.5% higher loan approval rate in affected counties, and negative sentiment events have the opposite effect of a smaller magnitude. The effect is stronger for marginal quality applications, where loan officers have more discretion. The extra loans approved on high-sentiment days experience higher defaults. Overall, our evidence suggests that mood fluctuations affect decisions of financial experts and generate long-lasting real effects.

JEL classification: A12, G02, G21

Keywords: mortgage, sentiment, loan officer, default

We gratefully acknowledge the helpful comments from seminar participants at the University of Michigan and Yale University. We also thank Caitlin Kearns for excellent research assistance.

One of the recent trends in financial markets has been an increasing replacement of human agents with automatic algorithms in a wide spectrum of financial decisions, ranging from stock trading and market making to credit card approvals. The advocates of this shift argue that it helps remove human sentiment from financial decisions and protects firms from possible judgment errors. Broadly defined, sentiment refers to changes in agents' mood and other psychological factors that are orthogonal to economic fundamentals. If sentiment indeed matters in financial decisions, it can have important economic consequences that extend beyond a single firm. For example, correlated changes in sentiment may generate cascading effects such as a market panic or a bank run, which affect entire regions and often invoke a policy response. Despite the potential significance of these effects, we know relatively little about how sentiment affects corporate financial decisions, whether it improves or impairs judgment, and what consequences it has on real economic activity. Our paper seeks to provide evidence in this direction by examining the role of sentiment in one of the fundamental economic decisions – credit origination.

We study how the sentiment of loan officers affects their decisions to approve or deny mortgage applications. Our focus on loan approvals is motivated by several factors. First, home mortgages involve most U.S. households and account for the majority of their financial commitments, indicating an important economic decision of broad public interest. Second, this setting allows us to observe key information available to the decision agent, the outcome and timing of the agent's decision, and the ex-post performance of originated loans. Third, the consequences of this economic decision have significant effects on other asset classes and the health of the financial system in general, as was illustrated during the recent crisis.

To measure the prevailing mood of decision agents, we use three proxies, which are constructed over our sample period of 1994-2010. The first is the outcome of major sporting events, which comprise the Super Bowl, the World Series, the NBA finals, and the Stanley Cup final. We define the positive (negative) sentiment event window as the two working days after the event in the home county of the winning (losing) team. The second proxy is the outcome of the American Idol Grand Finale, and the sentiment event window is defined analogously to that for the sporting events. The third proxy is major national holidays such as Thanksgiving, Christmas, and New Year's Eve. For all holidays, we define the positive sentiment event window as the two working days preceding the holiday, consistent with psychological evidence of strong positive sentiment before and during major holidays.[1]

The three sentiment proxies have several useful properties for identification. First, research in psychology shows that these types of events are associated with rapid and economically large changes in human mood, and that these changes are plausibly orthogonal to economic fundamentals. Second, the dichotomy between victories and losses offers a clear prediction about the directional changes in sentiment and allows us to test both positive and negative effects and evaluate their symmetry. Third, the event dates are clearly defined and specific to a geographic location (except for national holidays), allowing for both cross-sectional and time-series identification against a large control group.

Our empirical design allows us to address a number of identification challenges. First, we observe daily data on the number and quality of loan applications, which allow us to distinguish supply-side changes in credit approval decisions of loan officers from demand-side changes in application decisions of borrowers. This distinction is sharpened by a temporal gap of several weeks between the time when an application is submitted and when it is reviewed, a period spent by the bank on verifying and processing the application. Thus, at the time of application submission, both the exact time of its future review and the realization of future events are largely exogenous from the perspective of the borrower. Second, we observe the specific set of applications reviewed on a given day, thus distinguishing a loan officer's decision to review particular applications from the marginal changes in the approval rate of these applications relative to their hard data. Finally, we can trace the ex-post performance of a specific loan approved on a given date. These data enable us to test whether changes in sentiment are associated with better or worse decision outcomes and quantify their real effects.

Our main finding is that positive sentiment events lead to an increase in the loan approval rate of 4.5 percentage points, while negative sentiment events lead to a decline in the approval rate of 0.6 percentage points. Relative to the unconditional average approval rate of 83.3%, these estimates represent an increase of up to 5.4% and a decline of up to 0.7%, respectively. These marginal effects are reliably statistically significant and hold after

[1] For example, see Kramer (2010) for recent empirical evidence based on the gross national happiness index.

controlling for loan and borrower characteristics, time-series variation in loan demand, and unobservable county and lender effects.

In the cross-sectional analysis, we find that the effect of sentiment on mortgage approvals is stronger for loan applications of mediocre quality (e.g., borrowers with an annual income under $30,000), possibly because mortgage officers have more discretion on these applications. In the cross-section of sentiment events, we find that the strongest effects are associated with the outcomes of the Super Bowl, consistent with the official viewership data that indicate the largest following of this event.

Next, we investigate the ex-post performance of loans approved on sentiment days. We show that marginal-quality loans originated during positive sentiment event windows have a default rate that is 0.8 percentage points higher, compared to loans with similar observed characteristics originated in the same county on other days of the same quarter. This effect is economically large. The observed default rate on this subset of loans is about 16.7% greater than the default rate for loans of similar quality issued by the respective bank in the same county on non-event days. Using the estimated effect on mortgage defaults, we calculate an approximate cost of $900 million per year in excess defaults resulting from the extra loan approvals on sentiment days.

The evidence from mortgage defaults is consistent with findings in psychology that agents project their emotions from one activity (in our case, the sentiment events) to fundamentally unrelated professional tasks (in our case, loan approvals).[2] Psychology research predicts that under such circumstances, agents can make suboptimal decisions either because of a cognitive bias such as excessive optimism or a desire to share their emotions with others in their immediate community.

Overall, our study has several implications. First, our findings suggest that the sentiment of decision agents has a significant causal effect on their economic decisions. In particular, we document this effect in a setting with well-defined decision criteria, sophisticated financial experts, and observable outcomes, suggesting that the role of sentiment could be even greater in less structured economic environments. Moreover, while we

[2] For example, Wann, Dolan, Mcgeorge, and Allison (1994) show that wins and losses in important sporting events generate strong emotions that affect agents' fundamental views unrelated to sports. Schweitzer, Zillmann, Weaver, and Luttrell (1992) find that fans of the winning team express significantly more optimistic views about unrelated political and economic events compared to the fans of the losing team.

focus on discrete events for clean identification, agents' mood is likely to have a more pronounced, continuous effect on their daily decisions, as various factors cause swings in sentiment. Second, our evidence indicates that agents' sentiment can be highly correlated, at least during some time periods. To the extent that such correlations are persistent, they may amplify economic cycles by contributing to momentum during expansions and forestalling recovery during recessions. Finally, our findings demonstrate significant real effects – namely, large economic losses – associated with economic decisions during periods of strong sentiment. This evidence may explain a recent trend among some firms to impose a more structured decision environment in various settings, ranging from tighter regulation of proprietary traders to a greater reliance on standardized models in credit origination (Rajan, Seru, and Vig, 2010). However, while these tools can help agents make more informed decisions, they cannot match the flexibility and complexity of the human mind, suggesting that sentiment is likely to continue to play a role in key financial decisions. Overall, our study provides one of the first pieces of evidence on the causal effect of sentiment on corporate financial decisions.

The paper proceeds as follows. Section 1 discusses the related literature. Section 2 describes the institutional setting and sentiment proxies. Section 3 discusses the data and summary statistics. Section 4 provides the empirical results. Section 5 concludes.

1. Related Literature

Our paper is part of the literature in behavioral economics that studies the role of agents' psychological factors in economic decisions. Barberis and Thaler (2003) provide a comprehensive review of this research. Within this literature, our article is most closely related to the strand of research that studies the effect of agents' sentiment on economic behavior.

Previous research on agents' sentiment has focused primarily on its role in the stock market. To measure investor mood, previous studies have used sentiment proxies that broadly fall into three categories: (1) environmental conditions, (2) economic activity, and, most recently, (3) Internet activity. Among the proxies related to environmental conditions, earlier work has shown a positive effect of sunshine (Saunders 1993; Hirshleifer and Shumway 2003), temperature (Cao and Wei, 2005), and daylight (Kamstra, Kramer, and Levi,

2003) on stock returns. One identification challenge highlighted by this research is that a sentiment proxy and economic outcomes must be observable for the same set of agents. On the other hand, weather conditions vary significantly across investor locations, while investors' trading decisions are unobservable across locations, and stock prices are recorded only at the aggregate level. Several authors show that this issue may affect the interpretation of the evidence (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005). Another challenge highlighted in earlier work is that a sentiment proxy must have a clear directional prediction about its expected effect on economic activity. For example, it may be more challenging to predict the directional effect on stock prices for such variables as temperature (Cao and Wei, 2005) or lunar cycles (Yuan, Zheng, and Zhu, 2005).

Our identification strategy addresses both these challenges. First, we observe local economic activity at a highly-refined geographic level (e.g., the ZIP code of mortgage property for each application), permitting a clean match between an identification event and the observed decisions of affected agents. Second, we use a series of events that have been shown to drive powerful and directionally unambiguous changes in agents' sentiment. In particular, our research design enables us to distinguish between positive and negative sentiment, as well as between local sentiment events (such as the outcomes of sporting competitions) and national events (such as national holidays).

Another group of sentiment proxies used in previous research is based on observed economic activity. Examples of such measures include correlated trades of retail investors (Kumar and Lee, 2006; Kaniel, Saar, and Titman, 2008), composite sentiment indexes (Baker and Wurgler, 2006), and other measures inferred from economic indicators (surveyed in Baker and Wurgler, 2007). This research shows that investor sentiment explains return comovements and short-horizon returns, and that this effect is stronger for smaller stocks owned by retail investors. Most recently, the rapid development of search engines and social media has allowed researchers to construct sentiment measures based on Internet activity. Examples of these proxies include the content of Google searches (Da, Engelberg, and Gao, 2011) and Facebook status updates (Karabulut, 2011).

Sentiment proxies based on agents' economic activity and Internet messages provide important insights into agents' economic behavior. However, they often leave two open questions. First, what is the direction of the causal relationship between the sentiment proxy and the economic activity? On the one hand, agents' mood could drive economic outcomes. On the other hand, the prevailing economic conditions could affect agents' mood. For example, Karabulut (2011) argues that investor sentiment inferred from Facebook drives stock returns, while Cowgill and Zitzewitz (2009) argue that causality goes in the opposite direction – namely, a firm's stock performance changes the mood of its employees. Second, even if the effect of sentiment on economic activity is clearly established, what causes the variation in sentiment in the first place?

Our paper seeks to address both questions. In particular, by using identification events focused on sports, entertainment, or holidays, we establish a clear driver of sentiment changes supported by psychological evidence. Furthermore, by using sentiment drivers that are plausibly orthogonal to economic fundamentals, we provide causal evidence on the effect of sentiment on agents' economic decisions.

Overall, our article differs from the research on stock market sentiment along three dimensions. First, while market sentiment typically has a short-term effect on stock returns, which is quickly reversed (Tetlock 2007), our paper demonstrates that agents' mood may result in long-lasting, often permanent economic consequences. Second, while an investor's return on a given trade is unobservable, we trace the entire life of specific loans originated around sentiment events and provide evidence on whether sentiment improves or impairs judgment. Third, in contrast to the focus on asset pricing in prior research, we examine real effects on economic activity and estimate their costs.

Our article also contributes to the financial intermediation literature on the determinants of credit origination. Within this literature, our paper is part of a relatively small number of studies that examine the role of loan officers in credit markets. Recent work in this area shows that loan officers have significant decision power and discretion in credit approvals. As an example of loan officers' discretion, recent studies show that their decisions are significantly affected by personal rotations (Hertzberg, Liberti, and Paravisini, 2010), private incentives (Agarwal and Ben-David 2012; Tzioumis and Gee, 2012), regulatory concerns (Agarwal, Benmelech, Bergman, and Seru, 2012), and cultural proximity to the borrower (Fisman, Paravisini, and Vig, 2012).

To our knowledge, our paper is the first to uncover the role of loan officers' sentiment in credit approvals and to document its consequences on loan performance. In particular, our findings suggest that human emotions result in biased decisions even when these decisions are made by financial experts in one of the largest and most competitive consumer markets in the United States. More broadly, we show that the sentiment of financial intermediaries likely affects the mood and well-being of a large number of other economic agents, and identify one channel through which this effect operates.

Our paper also contributes to the broader literature on the role of behavioral factors in credit markets. From the perspective of financial consumers, Guiso, Sapienza, and Zingales (forthcoming) provide survey evidence that considerations of morality and trust reduce borrowers' propensity to declare default even when it is economically advantageous. Gross and Souleles (2002) use comprehensive data on credit card delinquencies and show that a lower stigma of personal bankruptcy explains a significant increase in default rates relative to fundamentals. From the perspective of capital providers, two recent papers use data from an online peer-to-peer lending market and show that micro-lending decisions are affected by subjective perceptions of borrowers' physical attractiveness (Ravina 2009) and trustworthiness (Duarte, Siegel, and Young, forthcoming) inferred from online photos.

Our paper extends this literature by studying the effect of human mood on mortgage origination. Human mood is uniquely distinct from other behavioral characteristics for at least two reasons. First, it is perhaps one of the most volatile, fast-changing personal traits, which stands in sharp contrast to highly-persistent factors such as morale, trustworthiness, and social stigma. This property makes human mood particularly interesting to study. It also enables a researcher to exploit rich time series variation in mood, while cleanly controlling for virtually all other characteristics that do not change on a daily basis. Second, human mood is heavily affected by exogenous factors, such as holidays, outcomes of sporting events, and personal events. This property offers an opportunity to instrument for human mood by using the variation in these exogenous events and provide causal inference. Interpreted broadly, our evidence suggests that by affecting the sentiment of decision agents, it may be possible to affect the outcomes of important economic decisions.

2. Sentiment Events and Institutional Setting

2.1 Sentiment Measures

To capture changes in investor mood, we use three types of event windows: (1) outcomes of major sporting events, (2) outcomes of the American Idol Competition, and (3) national holidays. This choice of events is motivated by previous research in various fields – from psychology to experimental economics – that these events cause powerful and directionally unambiguous changes in agents' mood. This subsection briefly reviews this motivating evidence and discusses our data.

Sporting Events

The first type of sentiment events comprises championship title games in the four most popular professional sports in the United States: football (Superbowl), basketball (NBA finals), baseball (Major League World Series), and hockey (Stanley Cup Finals). We focus on title games for two reasons. First, these games generate a clearly dichotomous outcome – one team wins the title, while the other loses. In contrast, during earlier stage games, it is less clear whether the result of a particular game is always positive or negative news. For example, during the regular season, the evaluation of any particular loss or victory depends on the outcomes of other games and team rankings (e.g., a victory may still leave a team out of the playoffs). Even during the playoffs, a victory merely allows a team to advance to the next stage. Second, title games constitute the most important games of the year followed by the largest number of residents in the team's home town. For example, the Superbowl is watched by 86% of adults between the ages of 25 and 50 in the teams' home towns, a demographic closest to loan officers. In contrast, earlier stage games generate only a small fraction of this audience. Since we cannot directly measure the mood of each loan officer, a wide following of title games indicates that our identifying events are likely to affect the largest number of individuals in the team's home county.

Evidence from psychology and experimental economics suggests that the outcomes of important sporting events have a powerful effect on agents' mood. For example, Wann, Dolan, Mcgeorge, and Allison (1994) show that wins and losses in important sporting events generate strong emotions that affect agents' fundamental views unrelated to sports. In a related study, Schweitzer, Zillmann, Weaver, and Luttrell (1992) find that fans of the winning team express significantly more optimistic views about unrelated political and economic events (such as the probability of a war in Iraq) compared to the fans of the losing team. If emotions from sporting events affect agents' optimism or pessimism about general economic conditions, we posit that they may also affect agents' credit approval decisions. For example, a spike in positive or negative sentiment may influence the mortgage officer's subjective estimates of future events, such as the likelihood of default by a given borrower or the future price dynamics of a given property.

Several research studies in finance find evidence consistent with the prediction that sporting events may change the agents' assessment of future economic events, as proxied by stock valuations. For example, Ashton, Gerrard, and Hudson (2003) find higher returns on the London Stock Exchange following a win by the England national football team and lower returns following a loss or a tie. Edmans, García, and Norli (2007) provide comprehensive evidence from 39 countries that a national soccer team loss is followed by a negative return in the nation's stock market. Chhaochharia, Korniotis, and Kumar (2012) show that a strong performance of a state's sports team is associated with local optimism, which contributes to faster economic recoveries.

We define a positive (negative) sentiment event window as the first two working days following the victory (loss) of the title game in each of the four main professional sports in the U.S. (football, basketball, hockey, and baseball). When the title series includes several games, we use the outcome of the last game that led to the title. The treated geographic regions include the home counties of the teams in the title game. Our results are similar if we use the definition of treated regions based on Metropolitan Statistical Areas (MSAs). The data on the outcomes of sporting events come from the web sites of the respective professional sport federations.

American Idol

Our second type of identification events is the outcome of the Grand Finale of the American Idol Music Contest. American Idol is a national singing competition that started in 2002. By 2005, the competition became the most widely-watched TV contest in the United States and retained this top position in each of the years between 2005 and 2011. As the only TV contest to achieve this record, American Idol is often described by media executives as the most impactful show in the history of television (Carter, 2007).

This identification event has several useful properties for our research design. First, similar to many professional sports, the title of American Idol is decided in a Grand Finale, held in late May, between two of the strongest participants that reach this final stage. Second, the winner of the competition is decided by a national vote via phone calls and text messages, indicating that the outcome of the vote is largely exogenous from the perspective of a particular individual or loan officer. In addition, this outcome is closely followed by a large fraction of residents. For example, during the latest season of American Idol, over 122.4 million votes were cast in the final round of the competition. Third, the outcome is highly unpredictable, and the difference in the fraction of vote between the losing and winning participant in the Grand Finale has been fewer than 5 percentage points in the majority of seasons. Finally, and perhaps most importantly, each participant is closely associated with his or her home town and has a strong home town following. For example, contestants make home town visits during the show, and they are typically greeted with a home town parade in their honor. The business press offers abundant evidence of strong emotional reactions to the outcomes of the competition in the home towns of the finalists (Beaty, 2011)

Analogously to our identification events based on sports, we define a positive (negative) sentiment event window as the first two working days following the victory (loss) of the Grand Finale contestant. The treated geographic regions include the home counties of the two finalists. The data on the outcomes of the American Idol Competition are collected from the website of the competition maintained by Fox Broadcasting Company.

Major National Holidays

Our third type of identification events constitutes the most widely celebrated national holidays: Thanksgiving, Christmas, and New Year's Eve. This choice of holidays is motivated by psychology research, which shows that these holidays are associated with strong positive emotions among most Americans. For example, Kramer (2010) shows that the days leading to and including these holidays are associated with a dramatic spike in the mood of Internet users, as inferred from their online status updates. In contrast, other holidays tend to have a much smaller effect on agents' mood or generate mood fluctuations that go in opposite directions for many subjects. For example, the author shows that Valentine's Day is associated with a dramatic increase in the mood of some agents and a large drop in the mood of others, likely depending on their personal relationship status. Therefore, we restrict our sample of holidays to the events that are associated with a large and unambiguous shift in the mood for a significant part of the population.

Previous research also suggests that agents' elevated mood and higher optimism around holidays may alter their economic behavior. For example, agents are more forgiving and more likely to provide formal and informal assistance to others around these events (Almeida et al., 2001). They also appear to be significantly more generous, as inferred from a large increase in charitable contributions around these events (Havens and Schervish, 1996). If these emotions carry over to a financial setting, we hypothesize that loan officers may be more optimistic and more forgiving with respect to potential borrowers right before major holidays.

We define a positive sentiment event window as the two working days preceding Thanksgiving, Christmas, and New Year's Eve. This measure is constructed at the national level, and treated observations include loan applications reviewed in all counties on the aforementioned dates.

2.2 Mortgage Approval Process

After a borrower submits a loan application, it is assigned to a loan officer. While the system of assigning an application to a loan officer varies across financial institutions, applications are typically reviewed by one of the officers at the local branch where the application is submitted. After an application is screened for completeness, the loan officer requests information on the borrower's financial history from the bank's internal records, credit bureaus, state agencies, and other sources. These data contain primarily hard information, which is used to complement and verify the client's application entries. For a typical application, the data collection process takes from three to five weeks. After all the data have arrived, the loan officer reviews the application and decides whether to approve the loan. Thus, there is a significant time lag between the time of application submission and the date of application review, which depends on how quickly various agencies provide the requested information.

When reviewing a loan application, the officer takes into account both hard and soft information about the borrower, uses personal judgment, and may also rely on loan underwriting software. In the vast majority of cases, the loan officer holds the ultimate decision power to approve or deny the application. Occasionally, a loan officer's supervisor may become involved if the applicant has a working relationship with the supervisor. If the loan application is approved, the loan officer provides the applicant an offer on the price (APR) for the loan. The borrower can decide whether to accept the loan or withdraw the application. Finally, if the borrower accepts the offer, the loan is originated. Thus, there are three main outcomes for the loan application process: denied, approved-not-accepted, and originated.

3. Data and Summary Statistics

3.1 Loan Data

Our data on mortgage loans come from three sources: (1) the Home Mortgage Disclosure Act (HMDA) database, (2) LPS Applied Analytics (formerly McDash), (3) CoreLogic LoanPerformance (LP).

Our primary data source for mortgage applications is the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. This dataset covers approximately 90 percent of mortgage lending in the U.S. (Dell'Ariccia, Igan, and Laeven, 2009), with the exception of mortgage applications submitted to the smallest banks (assets under $37 million) located in rural areas.[3] The unique feature of these data is the coverage of both approved and denied mortgages, which enables us to study loan approval decisions at the level of each application.

For each application in HMDA, we observe the exact date when the application is submitted and the date when the decision on the application is made. The HMDA data also provide the location of the property underlying each mortgage application. Other information available at the application level includes the characteristics of the borrower (e.g., income, gender, and race), the features of the loan (e.g., loan amount, loan type, and property location), the name of the financial institution, and the decision on the loan application. The identity of the loan officer is unobservable in our data.

We complement the data on application approvals from HMDA with the information on loan performance from LPS Applied Analytics. The LPS dataset provides loan-level information collected from residential

[3] According to the Home Mortgage Disclosure Act of 1975, most depository institutions must disclose data on applications for home mortgage loans, home improvement loans, and loan refinancing. A depository institution is required to report if it has any office or branch located in any metropolitan statistical area (MSAs) and meets the minimum threshold of asset size. For the year 2008, this reporting threshold was established at $37 million.

mortgage servicers. The data include loans from nine of the top ten servicers, and represent around two-thirds of the mortgage market in the United States, or more than 39 million active mortgage loans. The information is collected from mortgage servicers and includes agency and non-agency mortgage-backed securities as well as loans held in portfolio.

The LPS data provide extensive information about the loan, property, and borrower characteristics at the time of origination, as well as dynamically updated loan information subsequent to origination. Property-related variables include appraisal amount, geographic location, and property type (single-family residence, condo, or other type of property). Loan characteristics include origination amount, term to maturity, lien position, whether or not the loan is conventional, loan purpose (purchase or refinance), a lender-defined subprime flag, and the coupon rate on the mortgage. Credit-risk-related variables include the debt-to-income ratio, FICO credit score, loan-to-value (LTV) ratio of the borrower at origination, and the level of documentation provided.

Beyond the data that are available at origination, dynamically updated variables capture changes made to the loans after origination, as well as their performance at a monthly frequency. Variables of interest include coupon rates (which change for ARMs and have the potential to change for loan modifications), delinquency status (current, 31–60 days delinquent, 61–90 days delinquent, over 91 days delinquent, foreclosure, REO,[4] or paid off), investor type (held in portfolio; private securitization; GNMA, FNMA, and FHLMC; [5] GNMA buyout loans; Local Housing Authority; or Federal Home Loan Bank), and actual principal balance, as well as scheduled principal balance if the borrower pays according to the original terms of the loan.

One limitation of the LPS dataset is its scarce coverage of subprime loans. To address this issue, we complement the LPS data with the dataset from CoreLogic LoanPerformance, which focuses on the subprime mortgage market. The later dataset covers securitized subprime loans sold to non-GSEs and includes similar information on loan characteristics and loan performance as that contained in LPS. As a result, the combination of these two datasets allows us to achieve a broad coverage of the mortgage market.

[4] REO stands for real estate owned. Here the lender has taken ownership of the collateral property on which the loan was originally based.

[5] GNMA refers to *Government National Mortgage Association (Ginne Mae);* FNMA refers to Federal National Mortgage Association (Fannie Mae); and FHLMC refers to Federal Home Loan Mortgage Corporation (Freddie Mac).

In summary, the HMDA enable us to evaluate the loan approval process, while LPS and LoanPerformance provide information on the subsequent performance of originated loans. In addition, the merged dataset provides us with a combined set of borrower, lender, and loan characteristics from each of the three data vendors.

3.2 Sample construction

We begin our sample construction with the HMDA loan application registry from 1994 to 2010. To construct a homogenous sample of conventional mortgages, we exclude Farm Service Agency and Rural Housing Service loans. We also exclude applications with processing time greater than five months and applications processed on non-working days. These cases are rare and often indicate an error in the date recorded (e.g., a date which has not yet occurred, but which will fall on a non-working day in 2016).

The approved HMDA loan applications are matched to LPS and LoanPerformance on origination date, zip code, loan amount, loan type, loan purpose, occupancy type, and lien. Since LPS data are sparse during the earlier part of our sample period, this match reduces our sample size to approximately 8.5 million loans. In the matched sample, we introduce several additional filters to screen out observations with possible data errors. In particular, we exclude loan applications with FICO scores below 300 or greater than 900. We also eliminate loan observations with reported loan-to-value ratios above 100%.

Finally, we exclude broker-originated loans. This screen is motivated by the tendency of mortgage brokers to send their customers' applications to their financial partners or other banks located outside of the applicant's geographic area. As a result, the location of mortgage officers reviewing these applications is uncertain and cannot be inferred from the location of the mortgage property in our data. Following the same intuition, we also identify applications filed with lenders that do not have a branch in the county where the mortgage property is located and exclude these applications from the sample.[6] After these screens, we arrive at our final sample of approximately 4.8 million loans.

[6] The location of bank branches is collected from the Summary of Deposits dataset, which is published annually by the FDIC.

3.3 Descriptive statistics

Table I reports summary statistics for our sample, and Panel A in this table provides details on the classes of loan applications. The vast majority of applications (94.3%) are for conventional loans. The purpose of the loans is split between home purchase (39.9%) and refinancing (60.1%), and most applications (90.2%) are for owner-occupied properties. The originated loans in our sample are mostly fixed-interest loans (80.3%). Panel A also shows that 84.2% of the loans are for 1-4 family homes, and 65.3% are secured by a first lien. These summary statistics are largely consistent with the numbers reported in previous studies (e.g., Tzioumis and Gee, 2012).

In Panel B, we report application and loan characteristics. The average (median) loan application amount is $147,901 ($110,000). The average (median) household income is $84,162 ($65,000), and the average (median) loan-to-income ratio is 2.0 (1.8). Among all applications in our sample, 76.6% are originated, 16.9% are denied, and 6.5% are approved but not accepted by the borrower. Finally, we also provide summary statistics for the daily volume and processing times. The average daily volume of mortgage applications is 84,076 applications and the average application processing time is 37 days.

For the subset of originated mortgages in the HMDA-LPS, we observe detailed borrower and loan risk information that is unavailable for the entire HMDA sample. The average FICO score in our sample is 731, the average loan-to-value (LTV) ratio is 67.4%, the default rate (defined as 90-day delinquency or foreclosure within 24 months of origination) is 2.1%, and the average APR on originated loans is 5.8%.

Panel C reports the distribution of the 245 sentiment event days in our sample. Sentiment events are matched to loan applications based on two characteristics: (1) calendar date when the application decision was made and (2) geographic location, as proxied by county where the mortgage property is located.

4. Empirical Analysis

4.1 Univariate Results

We begin our empirical analysis by providing univariate evidence on the effect of positive and negative sentiment events on mortgage approval and default rates. Table II reports difference-in-means estimates of approval rates (Panel A) and default rates (Panels B and C) during sentiment event windows.

The average approval rate for positive sentiment and negative sentiment events is calculated across all applications submitted in treated counties in the two-day sentiment event window. For each type of sentiment, the nonevents include all applications submitted outside any two-day sentiment event window, as well as all applications within the two-day window that are submitted in untreated counties. To assure that our control group is unaffected by sentiment, we exclude untreated counties in the same state as the treated county during the two-day event window. The sentiment events are defined analogously for the subset of LPS loans in the difference-in-means estimates of default rates in Panels B and C.

The results in Panel A suggest that approval rates are on average higher for positive sentiment events and lower for negative sentiment events compared to nonevents. For positive (negative) sentiment events, the approval rates are 3.9 percentage points higher (5.1 percentage points lower) than for nonevents. On relative terms, approval rates are 4.7% higher (6.1% lower) on positive (negative) sentiment events compared to nonevents. Overall, as Panel A shows, approval rates are higher during positive sentiment events than during negative sentiment events. These differences are reliably statistically significant at the 1% level.

Panel B considers default rates. The point estimates suggest that default rates are 4.8% higher for loans approved during sentiment event windows in treated counties, as compared to untreated loans, and the difference is highly statistically significant at the 1% level. We do not find a statistically significant difference between default rates around negative sentiment events and nonevents. Overall, default rates are 10% higher for loans originated during positive sentiment event windows compared to those originated during negative sentiment event windows, but the difference between positive and negative sentiment events is not statistically significant at conventional levels.

In Panel C, we consider the subset of marginal quality loans, defined as *loans in which the* borrower's FICO score is between 620 and 750 and the loan-to-value (LTV) ratio is greater than 90%. We hypothesize that for this subset of loans, sentiment may have a larger effect on default rates because loan officer's discretion is likely more important for marginal borrowers (i.e., the less clear-cut cases). Consistent with our hypothesis, we find that default rates are 18.8% higher for loans approved during positive sentiment events compared to nonevents, and the difference is highly statistically significant at the 1% level. The magnitude of the effect (18.8%) for marginal loans is substantially larger than the effect for all loans (4.8%). Once again, we do not find a statistically significant difference between default rates during negative sentiment events compared to nonevents.

Next, we proceed with multivariate regression analysis, which we begin with a brief overview of our identification strategy.

4.2 Identification Strategy

To examine the role of mood in mortgage approvals, we estimate linear probability models of mortgage application approval in which the treated observations are the applications processed in counties during positive or negative sentiment event windows, as defined earlier.

The control group comprises all loan applications outside any event window, as well as all applications within the event window in untreated counties. To assure that our control group is unaffected by local sentiment, we exclude untreated counties in the same state as the treated county during the event window. To compare between sentiment events and nonevents, we estimate separate linear probability models for positive sentiment and negative sentiment events. Formally, our models are specified as follows:

$$Approval_{ictl} = \alpha_0 + \beta_1 PositiveSentiment_{ct} + \rho LoanToIncome_{ictl} + \lambda Controls_{ictl} + \varphi Month + \delta County_c + \tau EventTime_t + \gamma Lender_l + \varepsilon_{ict}$$

$$Approval_{ictl} = \alpha_0 + \beta_1 NegativeSentiment_{ct} + \rho LoanToIncome_{ictl} + \lambda Controls_{ictl} + \varphi Month + \delta County_c + \tau EventTime_t + \gamma Lender_l + \varepsilon_{ict}$$

where the dependent variable *Approval* is a dummy variable equal to one if loan application i to lender l for a property located in county c at event time t was approved by the lender and equal to zero if the application was denied. *Positive Sentiment* is a dummy equal to one on the two working days following a Sports or Entertainment event in the winning county and on the two working days before a national Holiday in all counties. *Negative Sentiment* is a dummy equal to one on the two working days following a Sports or Entertainment event in the losing county. *Controls* denotes a vector of dummies indicating loan type (conventional, FHA-insured, or VA-guaranteed), loan purpose (purchase or refinance), occupancy type, applicant race, and applicant sex.

To control for possible seasonal variation in loan approvals, we include monthly (*Month*) fixed effects in all our regressions. To absorb similar variation across weekdays, we also include weekday fixed effects in all our regressions. We further wish to control for time invariant unobservable determinants of loan approval rates. To this end, we include county (*County*) and lender (*Lender*) fixed effects in all our tests. These fixed effects absorb county-level and lender-level variation in loan quality and demand. Finally, all our regressions include event-time fixed effects (*EventTime*), defined as the minimum distance t in days from the date the application was processed to the date of the nearest event.

Thus, our regressions can be interpreted as difference-in-difference event-study estimates of average approval rates for a given lender at a given county around sentiment events. Specifically, we estimate the change in approval rates during the sentiment event windows, while holding constant the treated county and the lender.

We estimate similar linear probability models for the performance of originated loans, where the dependent variable, *Default,* is a dummy variable equal to one if the loan becomes ninety days delinquent, enters foreclosure, undergoes short sale, or becomes real estate owned within twenty-four months of origination. As discussed above and shown in Table II, we expect sentiment to mainly affect the default rates of marginal quality loans, which are loans whose ex-ante observable characteristics imply a nontrivial default risk. For such loans, the officer's positive sentiment may lead him to underestimate the default risk and consequently approve some risky loan applications that would normally be rejected. Conversely, negative sentiment may cause mortgage officers to overestimate risk and deny marginal applications which might otherwise be approved. Formally, we define

Marginal quality loan as a dummy variable equal to one if the borrower's FICO score is between 620 and 750 and the LTV ratio is greater than 90%, and estimate the following models:

$$
\begin{aligned}
Default_{ict} = {} & \alpha_0 + \beta_1 PositiveSentiment_{ct} + \beta_2 PositiveSentiment_{ct} \times MarginalQualityLoan_{ict} \\
& + \vartheta MarginalQualityLoan_{ict} + \rho LoanToIncome_{ict} + \gamma InterestRate_{ict} + \lambda Controls_{ict} \\
& + \varphi Month + \delta County_c + \tau EventTime_t + \varepsilon_{ict}
\end{aligned}
$$

$$
\begin{aligned}
Default_{ict} = {} & \alpha_0 + \beta_1 NegativeSentiment_{ct} + \beta_2 NegativeSentiment_{ct} \times MarginalQualityLoan_{ict} \\
& + \vartheta MarginalQualityLoan_{ict} + \rho LoanToIncome_{ict} + \gamma InterestRate_{ict} + \lambda Controls_{ict} \\
& + \varphi Month + \delta County_c + \tau EventTime_t + \varepsilon_{ict}
\end{aligned}
$$

The coefficient of interest in these models is β_2, which corresponds to the interaction terms $PositiveSentiment_{ct} \times MarginalQualityLoan_{ict}$ and $NegativeSentiment_{ct} \times MarginalQualityLoan_{ict}$. A positive coefficient β_2 implies that default rates are higher for marginal quality loans that were approved following sentiment events. Conversely, a negative coefficient on β_2 implies that default rates are lower for marginal quality loans that were approved following sentiment events. In the next subsection, we begin our multivariate analysis by investigating the effect of sentiment on the approval rate of mortgage applications.

4.3 Regression Evidence on Mortgage Approval Rates

In this subsection we run formal tests of the effect of sentiment on mortgage approval rates and report the results in Table III. The unit of observation in our analysis is a mortgage application submitted during our sample period of 1994-2010. The dependent variable in these tests is an indicator equal to 1 if the mortgage application is approved and 0 otherwise. The main independent variables of interest are the *Positive sentiment* and *Negative sentiment* dummies. The coefficient on these variables captures the effect of sentiment on approval rates.

The empirical results, summarized in Table III, show a significant increase (decline) in loan approval rates following positive (negative) sentiment events relative to nonevents. The coefficient on the term *Positive sentiment* is positive and statistically significant at the 1% level, whereas the coefficient on *Negative sentiment* is negative and significant at the 10% level. This evidence suggests that for a given lender in a given county, approval rates are higher during positive sentiment events and lower during negative sentiment events, controlling for loan and borrower characteristics. These findings are also consistent with the univariate evidence reported earlier.

The magnitudes of our point estimates are also economically substantial. The coefficient on *Positive sentiment* equals 0.045, implying an increase of 4.5 percentage points in approval rates following positive sentiment events. Conversely, the coefficients on *Negative sentiment* equals -0.006, implying a decline of 0.6 percentage points in approval rates. Relative to the unconditional average approval rate of 83.1%, these estimates represent an increase of 5.4% for positive sentiment and a decline of 0.7% for negative sentiment.

As noted above, we hypothesize that sentiment should have a stronger effect on approval rates of marginal quality loans. Since we do not observe borrowers' FICO scores for the full HMDA sample, we proxy for borrowers' risk using a *low income* dummy that takes on the value of one for borrowers whose annual income is lower than $30,000. Table IV estimates linear probability models of loan approval in which the sentiment dummies are interacted with the loan income indicator.

The results, reported in Table IV, are consistent with our hypothesis. Our findings suggest that positive sentiment has a substantially bigger effect on the approval rates of riskier loan applications, as proxied by the borrower's income. The coefficient on *Positive sentiment* equals 0.041, implying that approval rates increase by 4.1 percentage points for non-low-income borrowers. The coefficient on the interaction term *Positive sentiment x Low income indicator* equals 0.033, which implies that positive sentiment increases approval rates by 7.4 percentage points for low income borrowers. The difference of 3.3 percentage points between the two groups of borrowers is highly statistically significant at the 1% level, as implied by the p-value on the interaction term *Positive sentiment x Low income indicator*.

Column (2) shows that the effect of negative sentiment is also bigger for low-income borrowers, though the 1.9 percentage points difference between non-low-income and low-income borrowers is not statistically significant at conventional levels (p-value=13.8%).

We also test whether sentiment affects loan officers' decisions differently during periods of financial crisis and non-crisis periods. Table V reports these results. Our findings suggest that positive sentiment has a substantially larger effect on approval rates during crisis years. The coefficient on the interaction term *Positive sentiment x Financial crisis* equals 0.020, which implies that positive sentiment increases approval rates by 6.1 percentage points during crisis years (compared to 4.1 percentage points for non-crisis-years). The two percentage point difference between non-crisis and crisis years is highly statistically significant at the 1% level, as indicated by the p-value on the interaction term *Positive sentiment x Financial crisis.* Similarly, the coefficient on the interaction term *Negative sentiment x Financial crisis* implies that negative sentiment reduces approval rates by 8.5 percentage points during crisis years compared to non-crisis years.

4.4 Regression Evidence on Mortgage Defaults

In this subsection, we investigate the effect of sentiment on the default rate of originated mortgages. We hypothesize that positive sentiment may lead loan officers to underestimate the default risk associated with mortgage applications and approve marginal quality loans that would not be approved otherwise. Under this hypothesis, we should observe an increase in the default rate of marginal quality loans following positive sentiment events.

We also investigate the default rate of marginal quality loans that were processed during negative sentiment event windows. If the effects are symmetric, we should observe lower default rates around negative sentiment events. If, however, loan officers are able to screen out most of the easily-predictable defaults when unaffected by sentiment, we might not observe a decline in default rates when sentiment is negative.

We test these hypotheses by estimating the linear default models described above. The unit of observation in this analysis is a loan that was originated during our sample period of 1994-2010. The dependent variable in these tests is an indicator equal to 1 if the loan becomes ninety days delinquent, enters foreclosure, undergoes short sale, or becomes real estate owned within twenty-four months of origination. The variables of interest are the interaction terms *Positive sentiment x Marginal quality loan* and *Negative sentiment x Marginal quality loan.* The coefficients on these variables capture the effect of sentiment on the default rates of marginal quality loans, defined as loans in which the borrower's FICO score is between 620 and 750 and the loan-to-value (LTV) ratio is greater than 90%.

As before, our regressions control for loan type (conventional, FHA-insured, or VA-guaranteed), loan purpose (purchase or refinance), occupancy type, applicant race, and applicant sex. They further include fixed effects for the month, weekday, county, lender, and event-time. We estimate the effects over the 2-day window following the sentiment events. The results are reported in Table VI.

We find a positive coefficient on the interaction term *Positive sentiment x Marginal quality loan*, which suggests that the default rate of marginal quality loans processed following positive sentiment events is higher. These results are highly statistically and economically significant. Mortgages that were approved within two days of positive sentiment events are 0.8 percentage points more likely to default, and the effect is statistically significant at the 1% level. Compared to the unconditional mean default rate of 4.8% on marginal quality loans reported in Table I, this estimate represents an increase of approximately 16.7% in default rate. The effect of positive sentiment holds after controlling for observable risk characteristics such as FICO scores and loan-to-value (which enter the definition of the marginal quality loan indicator), as well the observed interest rate on the loan. The latter is particularly important since it implies that the effect of sentiment on the default rate holds even after accounting for any pricing adjustments on the loan.

In contrast, we do not find a statistically significant effect of negative sentiment events on the default rate of marginal quality loans. The coefficient on the interaction term *Negative sentiment x Marginal quality loan* is insignificant at conventional levels, and the point estimate is in fact positive. These findings are consistent with the hypothesis that when unaffected by sentiment, loan officers are able to reject loan applications with a systematically higher likelihood of default. Under this hypothesis, ex-post loan defaults are random, and therefore, rejecting more loan applications due to bad sentiment does not lower the default rate.

The control variables all have the predicted signs. Marginal quality loans, loans with higher loan-to-income ratios, and loans with higher interest rates, all have higher default rates. These coefficients are all highly statistically significant at the 1% level.

Taken together, our evidence suggests that sentiment affects mortgage approval rates: positive sentiment leads to a higher approval rate whereas negative sentiment leads to a lower approval rate. These effects, in turn, translate into a higher default rate of positive-sentiment loans. The effect, however, is muted for the default rate of negative-sentiment loans due to the everyday prudence of loan officers during nonevent days.

To provide an economy-wide estimate of the consequences of sentiment, we calculate the implied loss due to the "excess" default rate under simple assumptions. Given a daily application volume of 84,067 applications and an origination rate of 76.6%, the estimated number of originated loans per day equals 84,067 x 0.766 = 64,395 loans. An average loan amount of \$147,901 implies a daily average of 64,395 x \$147,901 = \$9,524,084,895 in the principal amount of originated loans. This translates into an average "excess" default of approximately 0.8% x \$9,524,084,895 = \$76,192,679 per positive event day. For the two-day window following each sentiment event, this number doubles to \$152,385,358. A conservative assumption of six days of strong sentiment per year (e.g., two-day windows before Thanksgiving, Christmas, and New Year's Eve) yields an economy-wide cost of the sentiment effect of over \$900 million per year.

5. Conclusion

This paper uses the daily variation in mortgage approvals across geographic regions as a laboratory to investigate the effects of sentiment on real economic outcomes. We estimate linear probability models of mortgage application approval rates and mortgage default rates in which the treated observations are the applications processed in counties affected by positive or negative sentiment events. Our findings suggest that positive sentiment increases mortgage approval rates, whereas negative sentiment decreases approval rates. We also find that marginal quality loans originated during positive sentiment events are more likely to default. These results hold after controlling for loan and borrower characteristics, time-series variation in loan quality and demand, and unobservable county and lender effects.

Taken together, our findings provide estimates of the causal effect of sentiment on economic decisions. We propose that the implications of our results extend beyond our empirical setting, which focuses on the decisions of loan officers around relatively infrequent sentiment events. To the extent that sentiment is shared by multiple agents (e.g., local communities, business sectors, or the entire market), it may explain common patterns in economic decisions and generate cascading effects. More broadly, managerial sentiment may also affect other important corporate decisions, such as mergers and acquisitions, security issuance, and other corporate policies, which offer avenues for future research.

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TABLE I
Summary Statistics

This table reports summary statistics for the data used in the analysis. The mortgage application data are from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. Data on originated loans are from LPS Applied Analytics, Inc. The HMDA sample includes applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. The LPS-HMDA matched sample includes loans that have been matched to a retail loan in LPS with a FICO score between 300 and 900 and a loan-to-value (LTV) ratio less than or equal to 1. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. *Default* is defined as 90-day delinquency or foreclosure within 24 months of origination.

Panel A: Loan Types

			HMDA loan applications				
Loan type		**Loan purpose**		**Occupancy**			
Conventional	0.943	Home purchase	0.399	Owner-occupied	0.902		
FHA-insured	0.046	Refinancing	0.601	Not owner-occupied	0.098		
VA-guaranteed	0.010					Observations:	53,346,770
			LPS-HMDA matched loans				
Product type		**Property type**		**Lien status**			
Fixed	0.803	1- to 4- family	0.842	First lien	0.653		
ARM	0.131	Condo	0.122	Second lien	0.028		
Balloon	0.019	Other	0.036				
Interest only	0.043						
Other	0.003					Observations:	4,835,431

Panel B: Loan and Borrower Characteristics

Variable	N	Mean	SD	25th percentile	Median	75th percentile
Loan amount	53,346,770	147,901	132,965	60,000	110,000	190,000
Applicant income	53,346,770	84,162	69,977	42,000	65,000	101,000
Loan-to-income ratio	53,346,770	2.020	1.524	1.038	1.806	2.694
FICO score	4,835,431	731	57	694	741	777
LTV ratio	4,835,431	0.674	0.217	0.546	0.732	0.800
Default (0/1)	4,835,431	0.021	0.142	0.000	0.000	0.000
Interest rate	4,835,305	5.764	1.119	5.125	5.750	6.375
Originated (0/1)	53,346,770	0.766	0.423	0.000	0.000	0.000
Denied (0/1)	53,346,770	0.169	0.375	0.000	0.000	0.000
Approved, not accepted (0/1)	53,346,770	0.065	0.246	0.000	0.000	0.000
Daily volume	53,346,770	84,076	44,278	50,970	76,828	108,882
Days to process	53,346,770	37	29	17	31	50

Panel C: Sentiment Events

Event name	N	Percent
American Idol	18	5.980
Major League	32	10.631
NBA	29	9.635
Stanley Cup	30	9.967
Superbowl	34	11.296
Christmas	34	11.296
New Year's	34	11.296
Thanksgiving	34	11.296

TABLE II
Univariate Evidence

This table reports difference in means estimates of the effect of sentiment on loan application approval rates (Panel A) and loan default rates (Panels B and C). The mortgage application data are from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. Data on originated loans are from LPS Applied Analytics, Inc. The HMDA sample includes applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. The LPS-HMDA matched sample includes loans that have been matched to a retail loan in LPS with a FICO score between 300 and 900 and a loan-to-value (LTV) ratio less than or equal to 1. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. *Default* is defined as 90-day delinquency or foreclosure within 24 months of origination. *Marginal quality loan* is a dummy variable equal to one if the borrower’s FICO score is between 620 and 750 and the loan-to-value (LTV) ratio is greater than 90%.

Panel A: Loan Application Approval Rates

Sentiment	Approval rate	Sentiment	Approval rate	Sentiment	Approval rate
Positive	0.869	Negative	0.779	Positive	0.869
None	0.830	None	0.830	Negative	0.779
Difference	0.039	Difference	-0.051	Difference	0.090
t-statistic	120.000	t-statistic	15.450	t-statistic	29.960
p-value	0.000	p-value	0.000	p-value	0.000

Panel B: Loan Default Rates

Sentiment	Default rate	Sentiment	Default rate	Sentiment	Default rate
Positive	0.022	Negative	0.020	Positive	0.022
None	0.021	None	0.021	Negative	0.020
Difference	0.001	Difference	-0.001	Difference	0.002
t-statistic	5.010	t-statistic	0.220	t-statistic	0.760
p-value	0.000	p-value	0.823	p-value	0.446

Panel C: Loan Default Rates for Marginal Quality Loans

Sentiment	Default rate	Sentiment	Default rate	Sentiment	Default rate
Positive	0.057	Negative	0.063	Positive	0.057
None	0.048	None	0.048	Negative	0.063
Difference	0.009	Difference	0.015	Difference	-0.006
t-statistic	4.080	t-statistic	0.668	t-statistic	0.270
p-value	0.000	p-value	0.823	p-value	0.786

TABLE III
Sentiment and Mortgage Approval Rates

This table reports estimates from linear probability models of the relation between sentiment and bank approval rates on mortgage applications. The dependent variable is an indicator equal to 1 if a loan was approved. The mortgage application data are from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. The sample includes applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. All regressions include month, county, lender, day-of-week, and event time fixed effects, as well as controls for applicant race and sex, loan purpose, loan type (conventional, FHA, or VA), and occupancy type. The p-values (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the county level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Model	(1)	(2)
Positive sentiment	0.045*** [0.000]	
Negative sentiment		-0.006* [0.051]
Log loan-to-income	-0.024*** [0.000]	-0.024*** [0.000]
N	53,346,770	53,346,770
Adjusted R^2	0.093	0.093

TABLE IV
Sentiment, Approval Rates, and Borrower Income

This table reports estimates from linear probability models of the relation between sentiment and bank approval rates on mortgage applications. The dependent variable is an indicator equal to 1 if a loan was approved. The mortgage application data are from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. The sample includes applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. *Low income* is a dummy equal to 1 is the borrower's income is lower than $30,000. All regressions include month, county, lender, day-of-week, and event time fixed effects, as well as controls for applicant race and sex, loan purpose, loan type (conventional, FHA, or VA), and occupancy type. The p-values (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the county level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Model	(1)	(2)
Positive sentiment	0.041*** [0.000]	
Positive sentiment x Low income indicator	0.033*** [0.000]	
Negative sentiment		-0.004 [0.170]
Negative sentiment x Low income indicator		-0.019 [0.138]
Low income indicator	-0.121*** [0.000]	-0.121*** [0.000]
Log loan-to-income	-0.013*** [0.000]	-0.013*** [0.000]
N	53,346,770	53,346,770
Adjusted R^2	0.102	0.102

TABLE V
Sentiment, Approval Rates, and the Financial Crisis

This table reports estimates from linear probability models of the relation between sentiment and bank approval rates on mortgage applications. The dependent variable is an indicator equal to 1 if a loan was approved. The mortgage application data are from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. The sample includes applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. *Financial crisis* is a dummy equal to 1 in the years 2007-2010. All regressions include month, county, lender, day-of-week, and event time fixed effects, as well as controls for applicant race and sex, loan purpose, loan type (conventional, FHA, or VA), and occupancy type. The p-values (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the county level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Model	(1)	(2)
Positive sentiment	0.041*** [0.000]	
Positive sentiment x Financial crisis	0.020*** [0.000]	
Negative sentiment		0.015*** [0.000]
Negative sentiment x Financial crisis		-0.085*** [0.000]
Log loan-to-income	-0.024*** [0.000]	-0.024*** [0.000]
N	53,346,770	53,346,770
Adjusted R^2	0.093	0.093

TABLE VI
Sentiment and Mortgage Default Rates

This table reports estimates from linear probability models of the relation between sentiment and mortgage default rates. The dependent variable is an indicator equal to 1 if the loan becomes ninety days delinquent, enters foreclosure, undergoes short sale, or becomes real estate owned within twenty-four months of origination. The sample includes originated loans from LPS Applied Analytics, Inc, which are matched to mortgage application data from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry. We include applications to insured banks with a local branch on all working days from 1994 to 2010. Home improvement and FSA/RHS applications are excluded, as are applications that took more than five months to close. The sample only includes loans with a FICO score between 300 and 900 and an LTV ratio less than or equal to 1. Sentiment events include entertainment (American Idol), sports (Major League Baseball, NBA, Stanley Cup, Superbowl), and holidays (Christmas, New Year's Day, and Thanksgiving). Treatment is at the county level; untreated counties in the same state as a treated county during the event period are dropped from the sample. *Positive sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the winning county and on the two working days preceding a holiday in any county. *Negative sentiment* is a dummy equal to one on the two working days following a sports or entertainment event in the losing county. *Marginal quality loan* is a dummy variable equal to one if the borrower's FICO score is between 620 and 750 and the loan-to-value (LTV) ratio is greater than 90%. *Interest rate* is the first observed interest rate on the loan in the LPS dataset. All regressions include month, county, lender, day-of-week, and event time fixed effects, as well as controls for applicant race and sex, loan purpose, loan type (conventional, FHA, or VA), and occupancy type. The p-values (in brackets) are based on standard errors that are heteroskedasticity consistent and clustered at the county level. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Model	(1)	(2)
Positive sentiment	-0.001 [0.283]	
Positive sentiment x Marginal quality loan	0.008*** [0.000]	
Negative sentiment		-0.001 [0.763]
Negative sentiment x Marginal quality loan		0.014 [0.328]
Marginal quality loan	0.010*** [0.000]	0.010*** [0.000]
Log loan-to-income	0.011*** [0.000]	0.011*** [0.000]
Interest rate	0.011*** [0.000]	0.011*** [0.000]
N	4,835,305	4,835,305
Adjusted R^2	0.047	0.047