Animal Spirits: Stock Market Volatility and Risk Aversion

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ABSTRACT

Using disaggregated data from a large commercial bank and a large retail insurance company, we find that daily stock market performance affects the decision-making of loan officers and demand for insurance products in a manner difficult to reconcile with rational choice theory. A one standard deviation increase in daily stock market volatility is associated with a 5.3% decrease in the probability of future default for contemporaneously approved loans, and a 6% increase in daily insurance sales. We explore a range of potential mechanisms and find the most support for stock market volatility inducing emotion-based changes in individuals' risk aversion.

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1 Introduction

> "Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of *animal spirits*... and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities "
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> - John Maynard Keynes, *General Theory of Employment, Interest and Money* (1936)

> "It is probably not an overstatement to say that visceral factors are more basic to daily functioning than the higher-level cognitive processes that are often assumed to underlie decision-making."
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> - George Loewenstein (2000)

A growing body of evidence from behavioral economics suggests that psychological factors have a significant impact on economically meaningful decisions (see DellaVigna (2009) for a review). Most of the existing research has focused on cognitive biases (i.e., anchoring, framing, gambler's fallacy, hyperbolic discounting, etc.). However, fundamental to psychology, but relatively understudied in economics, is the idea that visceral factors, or emotions experience at the time of decision-making, can have significant effects on individual decision-making (Loewenstein (2000)).

Using evidence from the field, we demonstrate that visceral factors can have a significant effect on individual decision-making in both professional and personal domains. Building on prior work showing that stock market conditions can affect both the emotional state and risk aversion of financial professionals in the lab (Lo and Repin (2002)), we first examine whether stock market performance can affect real world decision-making of loan officers via a psychological channel.

Using loan level data from a large Chinese bank, we examine the relationship between the performance of the Shanghai stock index and the decision by loan officers to approve commercial loan applications.[1] Due to institutional features of the bank, loan applications are as-if randomly assigned with respect to contemporaneous stock-market conditions.[2] As such, changes in loan-officer behavior can plausibly be attributed to contemporaneous changes in stock market conditions.

Controlling for both time trends and seasonal variation in market performance, we find that a one standard deviation increase in daily price volatility causes contemporaneously approved loans to be 5.3% less likely to eventually become distressed. In contrast, daily stock market returns do not have a statistically significant relationship with future loan distress. These results are robust across various sub-samples, to the use of alternate measures of both market volatility and loan distress, and to the inclusion of leads and lags of market performance. The coefficients for lead and lag measures of market performance are significantly smaller in magnitude than concurrent performance and never statistically significant, suggesting that the effect is both immediate and short lived.

We explore a range of explanations for our results. We first explore whether our results could be caused by learning, broadly defined, and find little empirical support for this hypothesis. Specifically, we find that a single day's market returns and volatility contains very little additional information about long run market conditions. As such, it contains

[1] Several factors make China a good environment to test whether stock market performance can viscerally affect decision-making. First, in China stock market participation extremely high in urban areas and individual traders tend to be very active. During our study period, individual investors are responsible for over 80% of total trading volume while holding only 30% of assets with an average portfolio turnover of over 400%. In addition, Shangban Chaogu or "on the job trading" is extremely prevalent, and recent surveys of white collar workers have found that over 90% say that some of their colleagues traded on the job and nearly half admit that they themselves traded stocks while at work. Indeed, this paper was inspired in part by complaints from managers of commercial banks in China about how much time and energy bank workers spent trading during office hours. In such an environment, stock market conditions are likely to be very salient to both potential buyers of insurance products and bank loan officers.

[2] First, there is a significant lag between the submission of a loan application and when they are reviewed. In conversations with bank management, we were told that the gap between when an application is submitted and when it is reviewed is several weeks; a one month turnaround is considered "fast." As such, the set of loan applications reviewed on any given day are unlikely to be driven by conditions on the day of review. Second, the task of reviewing a loan application is assigned by upper management at the start of each workday before the Shanghai Stock Market opens, and all such assignments are expected to be completed that day, so there is little room for time-shifting by either managers or loan officers across days in response to daily market conditions.

too little information about the credit worthiness of commercial borrowers to generate such large effects. In addition, the effect size is both larger in magnitude and more precisely estimated when we exclude extreme days in the tails of the distribution that more plausibly contain long-run persistent information about the economy.

We then explore the hypothesis that stock market volatility increases risk aversion among loan officers. If stock market volatility increase risk aversion, then loan officers should approve fewer, higher quality (i.e., less likely to become distressed) loans on high volatility days. Consistent with this idea, we find that the improvement in loan performance is realized through a decreases in the number of loans approved, driven by a decrease in (eventually) non-performing loans. An examination of firm observables shows that less than half of the decrease in distress rates associated with increases in volatility is explained by the differences in observable firm characteristics, suggesting that the effect is not due solely to an increased reliance on hard information. Taken together, these results suggest that loan officers are able to accurately identify and reject loans with a high risk of default, and exclude them at a higher rate during periods of market volatility.

To directly test the idea that stock-market volatility increases individual risk aversion, we use data from a large Chinese retail insurance firm to examine the relationship between stock market conditions and the demand for insurance policies. If stock market volatility increases individual risk aversion, the demand for insurance products should increase during periods of higher volatility. Consistent with our hypothesis of volatility-driven increases in risk-aversion, we find that a one standard deviation increase in daily price volatility leads to a 3-6% increase in insurance policy sales. We also find that contracts are more likely to be canceled if stock market volatility decreases during the 10-day government-mandated cooling-off period, during which individuals can costlessly cancel their insurance contracts. That is, individuals are more likely to buy insurance contacts when stock market volatility is high, and more likely to cancel recently purchased insurance policies if stock market volatility is lower during the cooling-off period relative to the date of purchase. This pattern of behavior is consistent with "the underappreciation of future visceral states and the hot-cold empathy gap" (Loewenstein (2000)) which can be thought of as the cause of "projection bias" (Loewenstein, O'Donoghue and Rabin (2003)).

Our paper makes several contributions. First, to the best of our knowledge, we provide the first field evidence that stock market performance can affect firm decision-making via psychological factors. Our paper builds upon a small, but important literature that examines the psychological impact of market performance on individuals in laboratory settings. Lo and Repin (2002), in which the authors study the responses of 10 experienced traders to contemporaneous market conditions, finds that "even the most seasoned trader exhibits significant emotional response, as measured by elevated levels of skin conductance and cardiovascular variables, during certain transient market events such as increased price volatility." Cohn, Engelmann, Fehr and Marechal (2015), also working with experienced traders, finds that subjects "primed with a financial bust were substantially more fearful and risk adverse than those primed with a boom." Our work contributes to this literature by extending their findings from the lab to the field.

Our paper is closely related to Guiso, Sapienza and Zingales (2018) which shows, using both survey and experimental evidence, that fear can generate significant increases in financial risk aversion. Using a combination of survey and detailed financial data, they show that risk aversion substantially increased in both qualitative and quantitative measures following the collapse of Lehman Brothers, and find market volatility induced "fear" to be the most likely mechanism. They provide further support for this hypothesis by running a lab experiment in which showing a "brief horrifying scene" from a horror movie led to subjects increasing their risk aversion. Their work represents some of the only direct evidence that psychological factors can affect an individual's risk aversion over time. Importantly, our findings, that normal market conditions can generate meaningful fluctuations in aggregate risk aversion, complements their results by extending the domain of such emotionally induced fluctuations from major financial crises, to the everyday.

Our paper is also related to Engelberg and Parsons (2016), who use daily hospital admissions data to document a strong inverse link between daily stock returns and contemporaneous hospital admissions due to "psychological conditions such as anxiety, panic disorder, and major depression." The paper presents this as evidence that rational "anticipation over future consumption directly influences instantaneous utility." In contrast, our findings suggest that stock market performance can significantly affect decision-making of loan officers and the demand for insurance products in the absence of changes to future consumption. That is stock market performance can affect individuals through a psychological channel, even in the absence of real changes to their expected utility.

More generally, our findings provide evidence that transient emotional states can affect how individuals (and firms) make economically meaningful decisions. In the domain of finance, the finding that the stock market can have a psychological effect on the actions of financial firms in a way that can directly affect the real economy squares the circle, providing evidence of a feedback channel that can exacerbate or dampen the effects of fundamental financial shocks. To the extent that our results are generalizable outside of our setting, they suggest that visceral responses to the stock market itself are a potential mechanism behind several puzzles including the equity premium puzzle and excess market volatility.

The rest of the paper proceeds as follows. The subsequent section describes the data used in the paper. Section 3 presents our empirical strategy and results on the effect of daily stock market movement on the characteristics and subsequent performance of contemporaneously approved loans. Section 4 explores several potential mechanisms for our empirical finding. Section 5 examines the impact of stock market volatility on insurance demand. Section 6 concludes.

2 Data

We have detailed information on commercial loans made by a large Chinese bank from 2006 through 2010. Our sample represent a randomly selected 10% subset of all loans made by the bank during our sample period. For each loan, we have loan size, loan disposition (as of 2017), province of origination, an indicator as to whether the loan originated at a province's headquarters, and starting in 2007, the credit rating of the borrowing firm.[3] While we make use of such data in our empirical analysis, due to the highly sensitive nature of the data and the desire of the bank to remain anonymous, we cannot reveal detailed statistics on specific loan or firm characteristics.

In addition to not being able to share details about loan and firm characteristics in the paper, the data comes with two other important limitations. First, the bank's computer system does not keep a record of rejected loan applications. Second, their software system, like in many other Chinese banks, does not record the date when the initial loan is approved, but rather when the loan is funded (i.e., funds are transferred to the company). In contrast, for loan extensions, since there is no transfer of funds, the exact date of approval is recorded. As such, we focus our analysis on loan extensions. In cases where a loan receives more than one extension, we limit our analysis to the first extension. Such loans represent a small but substantial portion of the banks loans, and provides us with a sample of 40,808 loans.

The bank divides each province into regions or prefectures (Fen Hang in Chinese). Within each region there is a main or central office, and several branch offices. While loans may originate from any office, in an effort to combat corruption, in 2005 the bank, like other banks in China, centralized loan approvals and instituted a requirement that all loans be approved by loan officers working in the main office of each banking region. At the start of each day, upper management in a district's central office assigns specific loan

[3]This is an internal credit rating made by the bank at the time of loan approval based on the S&P long term debt grading system.

applications to individual loan officers for review. There is no hard as set rule (e.g., FIFO) regarding the receipt of a loan application and assignment for review, but according to the bank the lag between receipt and review is typically several weeks, with a lag of one month viewed as "good speed." All assigned loan reviews are expected to be completed the day they are assigned, and the reviews are rarely, if ever, late.

In 1999, the Chinese government issued the "Guiding Principles for Loan Classification," (PBOC 1999) which among other regulations, required commercial banks in China to classify loans into one of 5 categories: Normal, Concerned, Substandard, Doubtful, and Loss. Normal loans are those for which the probability of loss is considered zero. Concerned indicates that while the borrower has the ability to replay the loan, there exist factors that have the potential to adversely affect the ability of the firm to make payments in the future, with a probability of default of less than 5%. Substandard status indicates that while the firm is making its scheduled payments, it has "obvious" problems and cannot repay the loan in full by relying on its normal operating income. Such loans are considered to have a loss rate of 30% to 50%. Doubtful loans are loans that are in default, but there is some probability that the loan is not a complete loss. Such loans are expected to have a loss rate of 50% to 75%. Loss loans are loans that are in default for which the expected loss rate is greater than 75%. Substandard, Doubtful, and Loss loans are officially defined as "bad loans" (Bu Liang Dai Kuan in Chinese) by Chinese bank regulators. Our preferred specification treats only loans in default (i.e., Doubtful and Loss loans) as distressed. In robustness check, we include loans classified as Substandard as being in distress, as well as excluding loans classified as Doubtful as in distress.

As our measure of stock market performance, we collect daily data for the Shanghai Stock Exchange Composite Index (SSECI) from the China Stock Market & Accounting Research (CSMAR) Database. Market returns are defined as the difference between the index's closing value and its previous closing value. For both simplicity and transparency, we use the square of the daily market return as the measure of market volatility, but as shown below, the results are robust to the use of alternate measures of intraday volatility. This information was merged on date with the loan data. While most extension loan extensions were approved on days on which the market was open, we drop the slightly fewer than 10% of approvals that occurred on days when the Shanghai Stock Market was closed, leaving us with a sample of 36,701 distinct loans. The large majority of loans in our final sample are for an amount that ranges from 200,000 to 15,000,000 Yuan (approximately $30,000 to $2,500,000 USD), and made to firms with credit ratings between BB to AA. Approximately 4% of these loans are classified by the bank as Loss, 4% as Doubtful, and 2% as Substandard.

Our insurance data is from a large Chinese insurance company. We have daily sales counts for a range of insurance products sold by the firm from 2011 through 2014. In addition, we have contract level information for all contracts sold in a small number ($N < 10$) of cities by the firm for the same time period. The detailed data includes date of purchase, the city of residence of the purchaser, size and length of the contract, gender of the purchaser, whether the policy is for the purchases or a family member, and cancelation information.[4] Dropping sales on days on which the Shanghai Stock Market was closed leaves us with a sample of 1.9 million insurance contracts. Of these, we have detailed contract level information, including on 353,924 contracts with an average cancelation rate of 9.1%

3 Empirical Strategy and Results

The key identifying assumption in our analysis is that the portfolio of loans reviewed by the bank is unrelated to that day's market conditions. One potential threat to our

[4]Due to the sensitive nature of the data, we cannot reveal the identities of the cities in our sample or provide disaggregated statistics.

identification strategy would be if contemporaneous market conditions affected the timing of when a firm applies for a loan extension. This channel is unlikely in our setting for several reasons. First, since most loan extensions are filed near the end of loan term, there is only limited flexibility in the timing of loan application submissions. Second, compared to reviewing a loan extension, completing the paperwork to apply for a loan extension is a relatively time consuming task. As such, unless potential loan applicants are sitting on completed or nearly completed applications, it is not likely that they would be able to respond to high frequency shocks. Finally, and most importantly, because of the nature of the loan approval process, there is significant delay (a minimum of three business days, but typically several weeks), between the submission of the application and its review. This, combined with the high-frequency nature of our key variables, means a firm wanting to 'time' their loan review would not only have to accurately predict both market conditions a month or more in the future, but also the exact date on which their loan would be reviewed.

A second threat to our identification strategy is if market conditions affect which applications a loan officer reviews. For example, loan officers may chose to put off reviewing difficult to assess applications on days with significant stock market activity. This concern is largely mitigated by the fact that loan officers are expected to complete the review of all assigned loan applications the day they are assigned. While the bank does not keep a record of the assignment date of loan applications, in conversations with bank management, not completing the review of a loan application on the day it was assigned would be considered an exceptional event.

A third threat to our identification strategy is if market conditions affect the type of cases managers assign to loan officers. That is while loan offices may be unable to time-shift their assignments, the managers who assign the loans may change their assignments based on contemporaneous market conditions. Such a possibility is unlikely for two reasons. First, since loan applications assignments are made at the start of the day (8.30am), they are made before the open of the Shanghai Stock Exchange (9.30am).[5] Second, since managers are unlikely to carefully review loan applications before assignment, their ability to discriminate across loan applications is extremely limited.

3.1 Effect of Stock Market Performance on Loan Performance

We first explore the relationship between daily returns and volatility of the Shanghai Stock Exchange and the performance of contemporaneously approved loans. Figure 1 plots the relationship between daily returns of the SSECI and the subsequent share of contemporaneously approved loans by day (panel a) and by 1 basis point bins (panel b). Both panels show a strongly symmetric relationship between market returns and the performance of contemporaneously approved loans. Figure 2 plots the relationship between the intraday volatility of the SSECI and the subsequent share of contemporaneously approved loans by day (panel a) and by bins (panel b). In both panels, the data shows a clear negative relationship between volatility and loan performance in the raw data.

We next subject the relationship between market performance and the performance contemporaneously approved loans to regression analysis. Our base specification for estimating the impact of stock market on the subsequent performance of loan extensions is given by the following equation:

$$Distress_i = \beta Return_t + \nu Volatility_t + X_{it}\gamma + D_t + \epsilon_{it}, \tag{1}$$

where $Distress_i$ is a dummy variable equal to 1 if the commercial loan which is granted an extension i approved on date t is marked as distressed by the bank. $Return_t$ is the daily return of the SSECI in percentage terms on date t, $Volatility_t$ is a measure of the intra-

[5]Because the entirety of China operates under a single time-zone, the location of an individual office does not affect this timing.

day volatility of the SSECI on date t. The vector X_{it} consists of loan and borrowing firm characteristics. These include the size of the loan, the district of origination, firm credit rating, ownership structure, and industry classification. D_{jt} are day-of-week, week-of-year, and year fixed effects, included to account for possible seasonal variation in loan applications. Standard errors are 2-way clustered on date and district. The main coefficients of interest are β and ν, which captures the effect of stock market returns and volatility on the subsequent performance of contemporaneously approved loan extensions.

The results of estimating Equation 1 are presented in Table I, and present a pattern of results consistent with the those visually apparent in figures 1 and 2. Column 1 examines the impact of daily returns on subsequent loan performance. The point estimate for β in column 1 indicates that a one standard deviation increase in the SSECI is associated with a 5.2% decrease in the probability of default for loans approved that day, though this relationship is not statistically significant. Column 2 examines the effect of daily volatility on loan performance, and finds a large and statistically significant negative relationship between volatility and the probability that the loan becomes financially distressed. The point estimate for ν indicates that a one standard deviation increase in intra-day market volatility is associated with a 8.6% decrease in the probability of the loan eventually is classified as distressed. Column 3 shows the results of a regression that includes both daily return and volatility, and find very similar point estimates to regressing each factor independently.

Column 4 reruns the regression shown in column 3, but includes leads and lags of both returns and volatility. Including leads and lags have virtually no effect on the coefficient representing the daily market returns. In addition, the coefficients for the leads and lags of both returns and volatility are much smaller than that for contemporaneous return and volatility and statistically indistinguishable from zero. In addition to serving as a placebo test, the fact that leads and lags do not have a significant effect on loan performance suggests that the timing of applications by firms is not likely a confounding factor as it would require an extremely high degree of precision by the firm. This result, which suggests that the psychological effects of market conditions operates at high frequencies, is consistent with the finding in Engelberg and Parsons (2016) that the effect of market conditions on hospitalizations for psychological conditions is "nearly instantaneous," and not subject to significant lags.

3.2 Robustness

In Table II, we present the results of various robustness checks on the results presented in Table I. We first examine the sensitivity of our results to different measures of volatility. In columns 1 and 2, we repeat the regression from Table I, column 3, using the measures of intraday market volatility as described in Parkinson (1980) and Rogers and Satchell (1991) respectively. We find that for both measures, there is a strong and statistically significant negative relationship between volatility and the probability that a loan approved that day becomes distressed. The magnitude of this relationship is also remarkably stable across all three volatility measures, with standard-deviation adjusted effect sizes of 0.0057, 0.0053 and 0.0052 for our base measure, Parkinson (1980) and Rogers and Satchell (1991) respectively.

In the next two columns, we examine the impact of using different definitions of financial distress. In our base specification, we classify only loans that are in default to be financially distressed. In column 3, we loosen our definition of distress to include "Substandard" loans. These are loans that are not in default as the firm has made all its scheduled payments, but are thought by the bank to be in significant danger of default. The point estimate is very similar to that of the base specification, and highly significant. In column 4, we exclude loans that are in default, but for which the bank expects a loss rate of between 50-75%, and include only those classified as "Loss" loans. Using this highly restrictive definition of financial distress decreases the size of both coefficients of interest by half.

We then explore the sensitivity of our results to days with unusually large swings by excluding days in which the market experiences extreme swings in either direction. One concern is that while most days contain little additional marginal information about the economy, certain extreme days contain significant information. To see if such days are driving our results, in columns 5 and 6, we rerun our main regression specification excluding days that correspond to the largest 1% and 5% swings in daily gains and losses. In both case, the coefficient for market return is largely unchanged and is not statistically significant at conventional levels. In contrast, the coefficient for intraday volatility is significantly larger strongly statistically significant. This result suggests not only that our volatility results are not driven by "extreme" days, but that such unusual days represent a break from the pattern observed during more ordinary times.

Finally, we attempt to mitigate the concern that our included time controls do not adequately account for seasonal variation. The results of Table 1, column 4 on leads and lags of market performance suggest that such seasonal variation is not driving our results. Nevertheless, in the final three columns of Table II, we repeat our main analysis using seasonal controls both coarser and finer than the one used in our main regression specification. Across all specifications, we find a strong and statistically significant negative relationship between intraday market volatility and the probability that a contemporaneously approved loan defaults.

3.2.1 Firm and Loan Characteristics

We next explore the impact of market performance on the type of loans that are contemporaneously approved. Table III presents the results of rerunning our basic regression with firm and loan characteristics as the dependent variable. Consistent with the results on loan performance, we find that market conditions affect approved loans mainly through intraday volatility. Higher intraday volatility is associated with the average approved loan being larger in size (column 1) and less likely to have originated outside a region's central office (column 2 - not statistically significant). In terms of firm characteristics, higher intraday volatility is associated with less state ownership (column 3) and more credit worthiness (column 4).

Taken together, these results provide evidence that when the market is volatile, loan officers approve loans that on average perform better than those that they approve on days when the market is less volatile. Loans approved on days with more market volatility are generally larger in size, less likely to be made to state owned firms, and made to firms with higher credit ratings. In addition some of the results offer some support for the idea that contemporaneous returns also affect loan officer decision-making, but these results are not very precise and should only be considered suggestive.

4 Potential Mechanisms

Our main empirical findings are that intraday market volatility causes loan officers to approve loans that perform better, are larger in size, and are made to companies with higher credit ratings. In this section we discuss several potential explanations for our findings.

4.1 Learning

Perhaps the most obvious explanation for these results is that intraday volatility provides information to the loan officers that changes their perception of the risk associated with the commercial loans under their review. The loans we study are medium to long term commercial loans, as such it is somewhat hard to imagine that the marginal information provided by one day is large enough to substantively change the probability of default. While we cannot directly test the information hypothesis, we can indirectly test it by seeing whether daily returns and volatility have any predictive power regarding stock market performance during our sample period. To do this, we run the regression

$$Cumulative\ Return_{t,\tau} = \beta Return_t + \nu Volatility_t + \gamma + D_t + \epsilon_{it}, \tag{2}$$

where $Cumulative\ Return_{t,\tau}$ is the percentage return of the Shanghai Stock Market over the period $\tau \in \{Month,\ Quarter,\ Half\text{-}Year,\ Year\}$ starting on date t, $Return_t$ is the percent return of the SSECI on date t, $Volatility_t$ is a measure of the intraday volatility on date t, and D_t are day-of-week, week-of-year, and year fixed effects.

The results of this analysis are presented in Table VI. They show that while daily returns have significant predictive power on cumulative returns for up to one quarter, for longer periods of time this effect disappears. More importantly, given our results, intraday volatility is uncorrelated with cumulative returns across any of the time periods we examine. These results indicate that the average day's market performance does not contain much information about the subsequent performance of market beyond a relatively short time horizon.

Another possibility is that while on most days, market performance does not include significant amounts of information about the long run performance of firms, there are certain days (e.g., market crashes, important earnings announcement days) that do contain a significant amounts of information, and that our results may be driven by such days. This concern is mitigated by Table II columns (5) and (6), which repeat our main analysis excluding days on which there were large market movements. Indeed, as noted above, the relationship between volatility and loan default is larger in magnitude when such extreme days are excluded from the analysis, indicating that the effect we find is driven by "ordinary," and not extreme, variation in intraday volatility.

Taken together, these results indicate that the marginal information provided by a single trading day cannot be driving our findings. Indeed, intraday market volatility is not predictive of future market returns even in relatively short periods of time. Under the assumption that market performance should contain more information about future market performance than the performance of commercial loans, these results provide relatively strong evidence against the idea that behaviors we document are the result of rational learning on the part of the loan officers.

4.2 Changes to Risk Aversion

An alternate mechanism for our results is that market conditions can lead to an emotion-based change in the utility function of loan officers. As hypothesized in Loewenstein (2000), shocks may cause individuals to have a visceral reaction that decreases their willingness to take on risk across domains. In our context, we hypothesize that market volatility induces a negative, visceral response in loan officers causing them to exhibit higher levels of risk aversion when evaluating loan applications. This idea has significant, albeit piecemeal, support in the existing literature. Most directly, Low and Repin (2002) find that market volatility causes strong emotional responses in even experienced professional traders as measured by skin conductance and cardiovascular measures.

If, as an emotional response to market volatility, loan officers exhibit increased risk aversion when evaluating loan applications, it should manifest through the rejection of marginal loans. That is the increase in loan performance on high volatility days should be driven by the rejection of the riskiest loans that would have been approved had market volatility been low. We test this prediction of the increased risk aversion hypothesis by examining the number and composition of loan extensions approved by day by the bank. To this end, we run the following regression:

$$Loans_t = \beta Return_t + \nu Volatility_t + \gamma + D_t + \epsilon_{it}, \tag{3}$$

where $Loans_t$ is the number of loans approved by the bank on date t, $Return_t$ is the percent return of the SSECI on date t, $Volatility_t$ is a measure of the intraday volatility on date t, and D_t are day-of-week, week-of-year, and year fixed effects.

Table V presents the results of this analysis. In the first two columns we use a Poisson regression framework to examine the impact of daily stock market returns and volatility on the total number of loan extensions (column 1), and number of loan extensions that eventually become default (column 2). Column 1 indicates that higher returns are associated with an increase in the number of approvals that day, while higher volatility is associated with fewer approvals. When we look at loans that eventually become distressed, the effect of returns disappears, while the coefficient for intraday volatility increases by a factor of 6. Columns 3 and 4 repeat this analysis using a negative binomial regression, and finds directionally similar results, but only the relationship between volatility and the number of loans that eventually default remains statistically significant.

4.3 Decreases in Effort

Another possible explanation for our findings is that market volatility distracts workers, causing them to spend less time and/or effort on evaluating loans, and that this decreased effort leads to the change in decision-making. The fact that Table V indicates that higher market volatility leads loan officers to essentially make better decisions (i.e., reject bad loans) may seem to some to be prima-fascia evidence against the distraction hypothesis.

However, in theory, decreased oerall efforts might lead to better decisions. For example, when pressed for time, loan officers may choose to reject marginal loans that require higher levels of effort to evaluate. Or alternatively, loan officers may be over-confident in their ability to discern good from bad loans, and that when distracted or pressed for time they rely more on "hard" information in making decisions. That is as documented in Paravisini and Schoar (2015), that putting increased weight on credit scores as opposed to "soft information" leads to better lending decisions by a for-profit bank. If in our setting, distraction similarly causes a defacto increase in the weight placed on"hard" information by causing loan officers to put less effort into analyzing applications, which may lead to better lending decisions.

As a test of this hypothesis, we examine the extent to which changes in firm observables (i.e., "hard information") explains the change in loan performance. If the change in loan performance is caused by an increased reliance on hard information, then the change in firm observables as documented Table III should account for the majority of the increase in loan performance. While such a finding would not allow us to rule out other explanations, its absence would be help rule it out.

We implement this test by repeating our basic analysis with an ever increasing set of firm and loan observables. The results of this analysis is presented in Table VI. Column 1 shows the impact of market conditions on loan performance with time fixed effects. Column 2 adds a dummy variable equal to one if the loan originated outside of a region's main branch, while column 3 adds fixed effects for each of the banking regions. Column 4 adds a dummy equal to one if the firm is a SOE. Columns 5 and 6, which include fixed effects for credit rating and industry type have a smaller number of observations because this data is available only for the latter parts of our sample period. Including firm and loan observables reduces the magnitude of the coefficient on intraday volatility, indicating that changes in firm observables do explain part, but not all, of the increase in loan performance.

Overall, these results provide at best weak evidence against the distraction hypothesis and illustrate in part the difficulty in differentiating between changes in risk aversion and changes to the decision-making process of loan officers more generally. As such, in the following section we attempt to directly test for stock market volatility induced changes in risk aversion by examining the relationship between market volatility and the demand for insurance.

5 Stock Market Performance and Insurance Demand

While the results above (on days with high market volatility the bank approves fewer loans, and importantly this decrease is driven by the rejection of loans with a higher probability of default) are consistent with volatility induced risk aversion, they are not dispositive. Therefore, to more directly test for volatility induced changes in risk aversion, we next examine the impact of stock market performance on the demand for insurance.

If market volatility increases individual risk aversion, the demand for insurance should be positively correlated with market volatility. We explore this idea by examining the relationship between intraday stock market volatility and the number insurance products sold by a large Chinese insurance company. Importantly for our analysis, the firm changes prices and advertising intensity very infrequently, and insurance purchases are consumer driven and not the result of direct sales (see Chang, Huang and Wang 2018 for a more details). As such, the relationship between stock market volatility and insurance sales can be plausibly interpreted as volatility induced changes in the demand for insurance. We analyze this relationship using the following regression:

$$log(Sales_t) = \beta Return_t + \nu Volatility_t + D_t + \epsilon_{it}, \tag{4}$$

where $Sales_t$ is the number of life and annuity policies sold by firm on date t, $Return_t$ is the daily return of the SSECI in percentage terms on date t, and $Volatility_t$ is a measure of the intraday volatility of the SSECI and D_{jt} are day-of-week, week-of-year, and year fixed effects. As before, the main coefficient of interest is ν, which captures the effect of stock market volatility the demand for insurance products.

The results of this regression are shown in Table 7. Consistent with the increased risk-aversion hypothesis, the results show that daily stock market volatility has a strong, positive impact on contemporaneous demand for insurance products across four different measures of market volatility. In column 1, volatility is measured as the average volatility the day of and the day before purchase. This is our preferred measure of volatility in this context because unlike the case of loan approval examined above, there can be a delay between the decision to purchase insurance and the actual buy (see Chang, Huang and Wang 2018 for a more detailed discussion). Column 2 uses the date-of-purchase volatility, while Columns 3 and 4 use the alternate measures of volatility described in Parkinson (1980) and Rogers and Satchell (1991).

The coefficient from column 1 indicates that a one standard deviation increase in daily volatility is associated with a 6% increase in the number of insurance contracts sold that day. Column 2 uses the date-of-purchase volatility, and finds that a one standard deviation increase in volatility leading to a 3.4% increase in the number of insurance contracts sold that day. while the coefficients in columns 3 and 4 indicate that a one standard deviation increase in intraday volatility increases same-day insurance sales by 4.2% and 5.3%, respectively. Daily market returns, on the other hand, have no appreciable impact on the demand for insurance across all four specifications.

We next examine the effect of daily stock market volatility on insurance cancellations as another test of the volatility induced risk aversion hypothesis. If individuals were induced to buy insurance due to high market volatility, decreases in volatility during the 10-day cost-free refund period should be associated with an increase in cancellations of insurance policies. This is essentially the key empirical test in Chang, Huang and Wang 2018 for testing whether idiosyncratic and ephemeral (i.e., non-informative) environmental factors have an effect on the demand for insurance, since such a pattern of reversals make it even less likely that such changes are driven by non-psychological factors. Following Chang, Huang and Wang 2018, we analyzing cancellations using the following regression specification:

$$Cancel_{ijt} = f(volatility_t, ..., volatility_{t+11})\beta + C_i b + X_{jt}\gamma + D_{jt} + \epsilon_{jt}, \tag{5}$$

where $Cancel_{ijt}$ is a dummy variable that equals 1 if individual i in city j cancels an insurance contract purchased on date t within 10 days of purchase.[6] $volatility_t$ is intraday stock market volatility, and ($volatility_{t+1,...,t+11}$) are the 11 leads of daily volatility. C_i includes controls for policy characteristics: the cost of the contract, the gender of the policyholder, whether the insurance was purchased for oneself or another family member, and the length of the insurance contract period. D_{jt} are day-of-week, week, year and city fixed effects designed to capture trends both within a week and over time. Standard errors are clustered on city*date.

We use two different specifications to capture the effect of volatility during the cooling-off period (CoP) on cancellation rates. Our first specification directly tests if cancellations are affected by differences in stock market volatility during the times when the purchase and cancellation decisions are made.

Specifically we replace stock market volatility with a measure of the *change* in volatility during the cooling off period relative to order-date volatility (Relative volatility). That is we run the regression

$$Cancel_{ijt} = \beta(Relative\ volatility_t) + C_i b + X_{jt}\gamma + D_{jt} + \epsilon_{jt}, \tag{6}$$

where

$$Relative\ volatility_{ijt} = (\sum_{\tau=1}^{11} \frac{1}{11} volatility_{ij,t+\tau} - volatility_{ijt}). \tag{7}$$

That is we measure the effect of the average volatility during the CoP normalizing the order-date volatility to zero.

The second specification replaces *Relative volatility* with contemporaneous volatility

[6]Although the legally mandated cooling-off period is 10 days, the firm does not appear to strictly enforce the 10-day rule. Consequently, a significant number of cancellations occur 11 days after purchase. Limiting the analysis to a 10-day post-purchase period generates similar results.

and a dummy variable that indicates whether the average stock market volatility during the cooling off period is *lower* than on the purchase date. In this case, $Relative\ volatility_t$ is replaced by $volatility_t$ and an indicator variable equal to 1 if $Relative\ volatility_t < volatility_t$.

Table 8, column 1 presents the result of regression relative volatility on cancellations. The coefficient of interest is negative and statistically significant, indicating a negative relationship between relative volatility and cancellations. This indicates that decreases in volatility relative to order-date volatility leads to increase in the probability of cancellation. Column 2 repeats the analysis, but with a dummy variable for whether the average daily volatility is lower during the cooling-off period relative to purchase-date volatility. Significantly, the order-date volatility is small and statistically insignificant, indicating that order-date volatility does not in and of itself have a first order effect cancellations. In contrast, the coefficient for the dummy indicating that average volatility is lower during the cooling-off period relative to the order-date level is large, positive and statistically significant indicating that a drop in volatility post-purchase is associated with a 8.8% increase the probability of cancellation.

Taken together, these results suggest that the demand for insurance, and thus risk aversion, is positively correlated with stock market volatility, leading to more sales on high volatility days and more cancellations when stock market volatility decreases *relative* immediately after purchase.

6 Conclusion

Our main empirical findings are that daily market conditions impact loan officer decisions far out of proportion to any potential informational content. Loans approved on days with high volatility are associated with lower default rates, with the decrease driven by the rejection of risker, marginal loans. Approximately half of the increase in performance is explained by changes in firm and loan observables, with high volatility associated with larger average loan size, a decreased probability of state ownership, and higher borrowing firm credit ratings.

We explore a range of potential mechanisms and find the most support for the idea that stock market performance impacts the risk aversion displayed by loan officers when reviewing loan applications. To directly test the idea that stock market volatility can increase the risk aversion of stock market participants, we examine the relationship between stock market volatility and the demand for insurance products, and find that high volatility days are associated with an increase in the demand for insurance products. In addition, we find that conditional on purchase, decreases in market volatility relative to the purchase-date levels leads to an increase in the cancellation rate.

These results suggest that visceral responses to uninformative environmental factors can have an economically meaningful effect on decision-making by both individuals and firms. Specifically, that the ”significant emotional response” to price volatility documented by Lo and Repin (2002) in the lab, occurs in the field, and that this emotional response affects their decision-making in other domains. These results provide evidence in support of the hypothesis in Lowenstein (2000) that emotion can affect decision-making across domains, in this case by increasing risk aversion of loan officers and buyers of insurance in a manner consistent with the “fear” channel documented in Guiso, Sapienza and Zingales (2018).

Because our study looks at the behavior of financial professionals, our results provide evidence of a potentially psychological channel through which the stock market can significantly affect the real economy. Importantly, our result suggest that ordinary day-to-day variation in stock market performance can cause meaningful changes in risk-aversion, even among financial professionals. That is while the stock market is not the real economy, stock market movements can affect the economy by changing how individuals feel about risk. Such a finding has important implications for several asset pricing puzzles, including serving as a mechanism behind the large variation in aggregate risk aversion implied by historic data (Campbell and Cochrane (1999)).

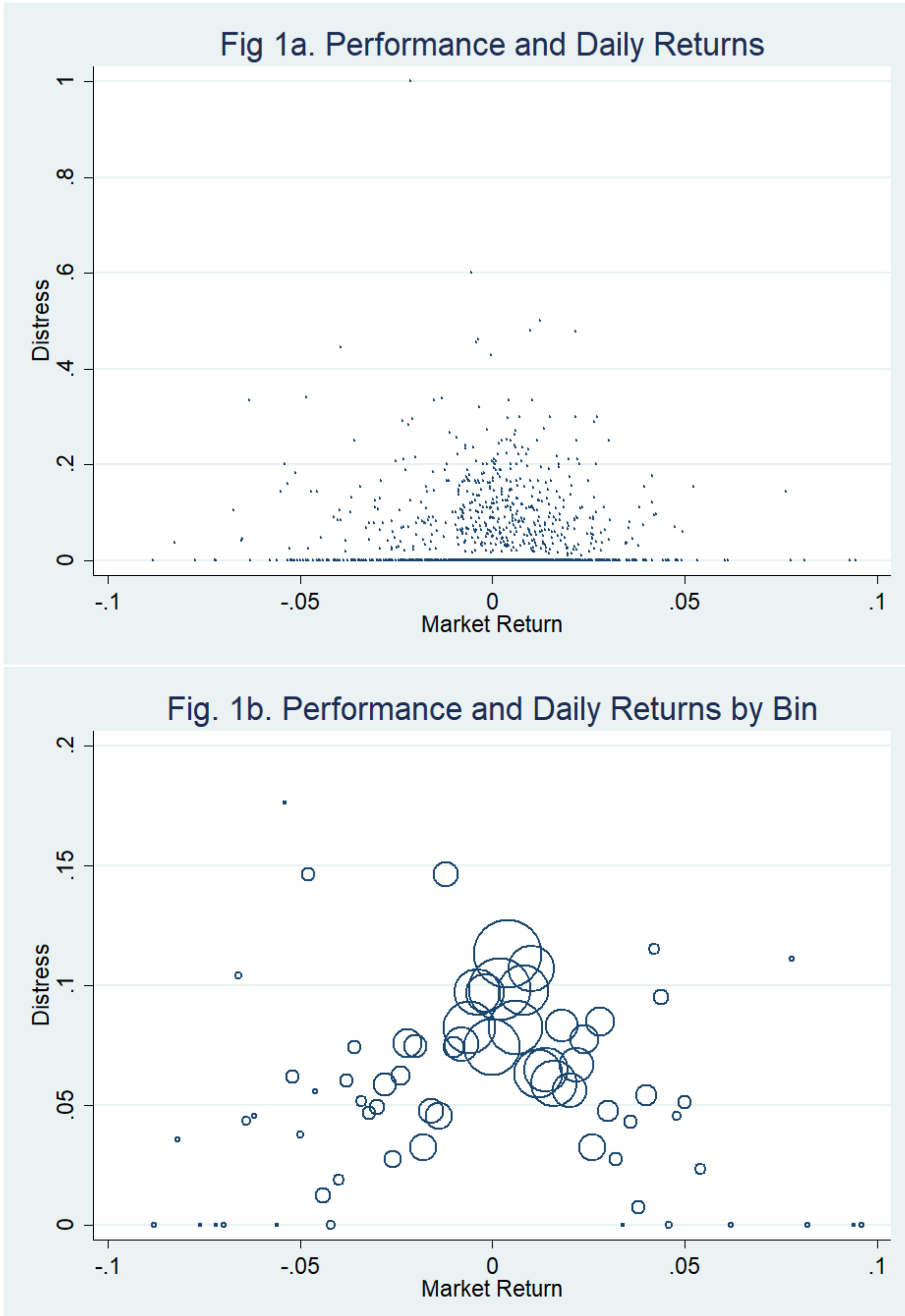

Figure 1. Loan Distress and Daily Market Return

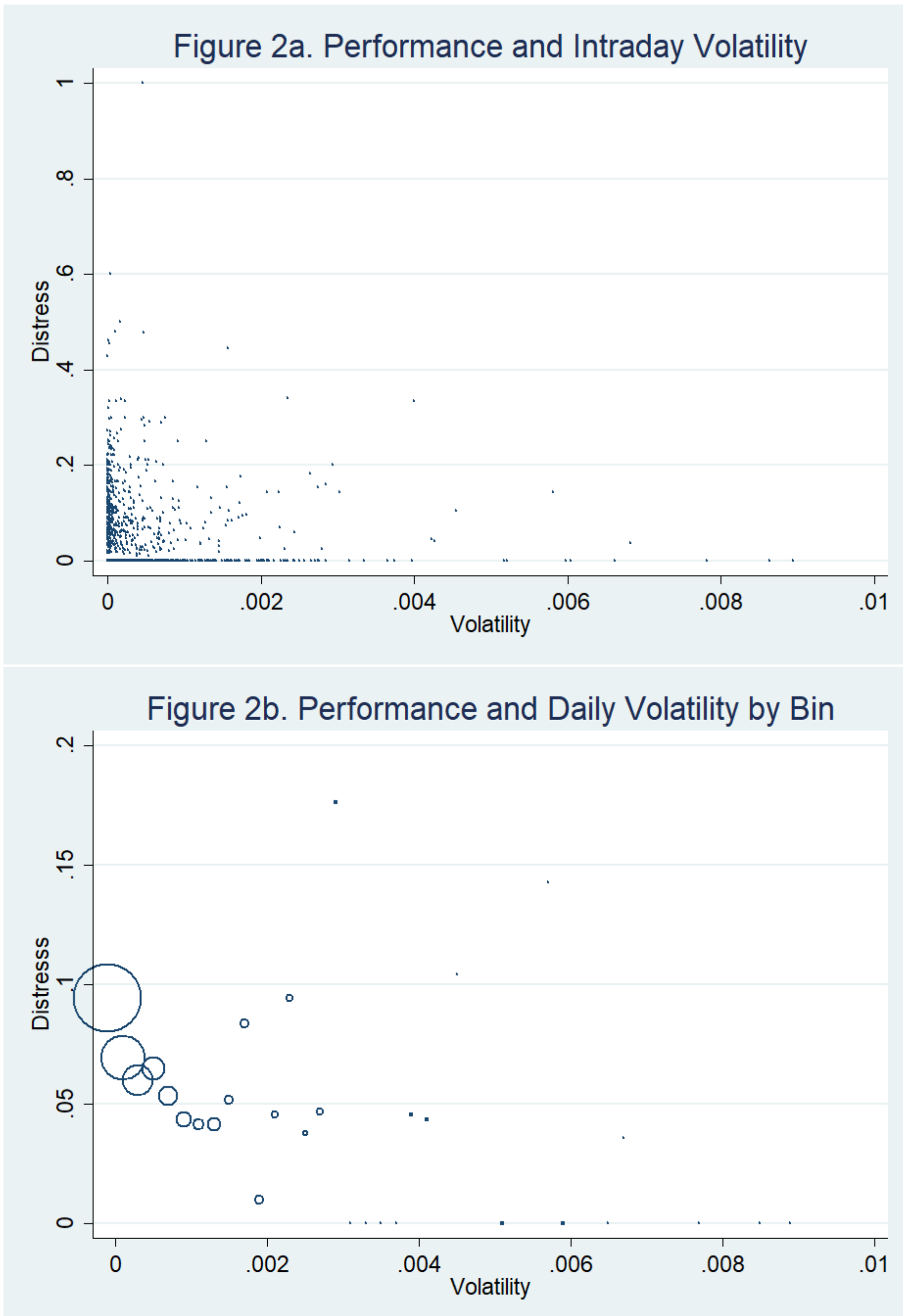

Figure 2. Loan Distress and Intraday Market Volatility

Table I
Loan Performance

Dependent Variable: Indicator equal to 1 if loan defaults

	(1)	(2)	(3)	(4)
Return	-0.2003		-0.2231+	-0.2031
	(0.1301)		(0.1300)	(0.1335)
Volatility		-8.2216**	-8.6089**	-8.2881**
		(1.9390)	(2.0487)	(2.3098)
Return t-1				0.0152
				(0.1200)
Return t+1				0.0245
				(0.1536)
Volatility t-1				-3.5985
				(3.1128)
Volatility t+1				-1.7226
				(1.6031)
Adjusted R-squared	0.0468	0.0471	0.0473	0.0474
Observations	36,701	36,701	36,701	36,701

Notes: All columns present the results from ordinary least square regressions. All regressions included controls for market open, day-of-week, week-of-year and year. Standard errors are 2-way clustered on date and region.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table II
Loan Performance Robustness

Dependent Variable: Indicator equal to 1 if loan defaults

	Volatility Measures		Distress Measures		Truncated Samples		Time Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Return	-0.2252+	-0.0842	-0.2332+	-0.1149	-0.2636	-0.2436	-0.2618+	-0.1598	-0.1260
	(0.1267)	(0.1457)	(0.1295)	(0.1124)	(0.2212)	(0.1700)	(0.1354)	(0.1287)	(0.0936)
Volatility	-0.3776**	-0.4740*	-8.8976**	-3.9954+	-21.4900**	-13.6567**	-8.9100**	-4.4512*	-3.2329*
	(0.1297)	(0.1988)	(2.3606)	(2.1804)	(4.5667)	(4.3545)	(2.4090)	(1.7713)	(1.5003)
Adjusted R-squared	0.0471	0.0471	0.0566	0.0383	0.0485	0.0476	0.0362	0.0453	0.0640
Observations	36,701	36,701	36,701	36,701	34,886	36,292	36,701	36,701	36,701

Notes: All columns present the results from ordinary least square regressions. Columns (1) and (2) use the intraday volatilty measures as described in Parkinson (1980) and Rogers and Satchell (1991) respectively. Column (3) includes loans classified as Sub-loan, Doubtful and Loss and being in distress. Column (4) includes only loans classified as Loss as being in distress. Columns (5) and (6) drop days corresponding to the top 1% and 5% of the distribution of daily volatility. All regressions include a control for market open. Regressions in columns (1) through (6) included dummy variables for day-of-week, week-of-year and year. In columns (7), (8), and (9) week-of-year and year fixed effects are replaced with fixed effects for month and year, month-by-year and week-by-year respectively. Standard errors are 2-way clustered on date and region.

Table III
Firm and Loan Characteristics

	Loan Size	*Branch*	*State Owned*	*Credit Rating*
	(1)	(2)	(3)	(4)
Return	2.2901+	0.0512	0.1288	0.1693
	(1.3483)	(0.2382)	(0.2262)	(2.1519)
Volatility	80.5430*	-9.8771	-11.3418*	136.1311**
	(36.5730)	(6.4830)	(5.5163)	(51.7379)
Adjusted R-squared	0.1448	0.0183	0.0317	0.1111
Observations	36,701	36,701	36,701	17,865

Notes: All columns present the results from ordinary least square regressions. Loan size is the log of the loan amount in RMB. County branch is a dummy equal to 1 if the loan originated from outside a region's main office. State owned is a dummy equal to one if the firm is a SOE. Credit rating is a numerical rating between 0 and 11, with higher numbers indicating higher credit worthiness. All regressions included controls for market open, day-of-week, week-of-year and year. Standard errors are 2-way clustered on date and region.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table IV
Daily Marginal Information

Dependent Variable: Percent Cumulative Return

	One Month (1)	One Quarter (2)	Half Year (3)	One Year (4)
Return	0.6755**	0.4234*	0.4420	0.1861
	(0.1322)	(0.2100)	(0.2958)	(0.3063)
Volatility	0.9277	3.6754	-2.0021	-7.5667
	(3.4252)	(4.8357)	(6.6647)	(6.7833)
Adjusted R-squared	0.4474	0.6665	0.7350	0.9430
Observations	1,092	1,063	999	744

Notes: All columns present the results from ordinary least square regressions with robust standard errors. All regressions included controls for market open, day-of-week, week-of-year and year.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table V
Number of Loan Extensions

	Poisson		*Negative Binomial*	
	All	*Defaulted*	*All*	*Defaulted*
	(1)	(2)	(3)	(4)
Return	0.7647*	-1.8264	0.3213	-3.2998
	(0.3030)	(1.3176)	(0.8729)	(2.1995)
Volatility	-30.039**	-182.079**	-4.2357	-160.998**
	(8.0903)	(41.3257)	(21.0587)	(58.5218)
Pseudo R-squared	0.5904	0.6116	0.1274	0.2567
Observations	1,215	1,215	1,215	1,215

Notes: The dependent variable for columns 1 and 3 is the total number of daily loan extention. The dependent variable for columns 2 and 4 is the total number of daily loan extensions approved that eventually default. All regressions included controls for market open, day-of-week, week-of-year and year.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table VI
Loan Performance and Firm and Loan Characteristics

Dependent Variable: Indicator equal to 1 if loan defaults

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Return	-0.2231+	-0.2261+	-0.2035+	-0.1998	-0.1705	-0.0157	-0.1087
	(0.1300)	(0.1236)	(0.1207)	(0.1232)	(0.1158)	(0.1462)	(0.1145)
Volatility	-8.6089**	-8.0186**	-6.4656**	-6.6124**	-5.4566**	-5.6375**	-4.6584**
	(2.0487)	(1.9228)	(1.7052)	(1.6394)	(1.3580)	(1.2067)	(1.2026)
Adjusted R-squared	0.0473	0.0576	0.1712	0.1721	0.1796	0.1454	0.1916
Observations	36,701	36,701	36,701	36,701	36,701	17,865	17,865
Branch		✓	✓	✓	✓	✓	✓
Region FEs			✓	✓	✓	✓	✓
State Owned				✓	✓	✓	✓
Loan Size					✓	✓	✓
Credit Ratings						✓	✓
Industry FEs							✓

Notes: All columns present the results from ordinary least square regressions. All regressions include a control for marketv open, day-of-week, week-of-year and year. Standard errors are 2-way clustered on date and region.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table VII
Demand for Insurance

	(1)	(2)	(3)	(4)
Return	-0.0951	-0.3465	-0.4124	-2.5175
	(1.2512)	(1.2534)	(1.2568)	(1.4149)
Volatility	135.741**	243.232**	1.5023**	7.3098**
	(52.105)	(70.866)	(0.4858)	(2.0937)
R-squared	0.0463	0.0467	0.0466	0.0467
Observations	8,729	8,729	8,729	8,729

Notes: The dependent variable is the log of the total number of life insurance and annuity contracts sold on a given day. Columns (1) and (2) calculates volatility using the square of daily return, while columns (3) and (4) use the volatilty measures described in Parkinson (1980) and Rogers and Satchell (1991) respectively. Columns (1), (3), and (4) are measures of purchase-date volatility. Column (2) is the average volatility on the date of, and the date before purchase. All regressions included controls for day-of-week, week-of-year and year.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table VIII
The Effect of Volatility on Cancellations

Dependent Variable: Indicator equal to 1 if contract is canceled		
% of Contracts canceled	9.05%	9.05%
Relative volatility	-18.842**	
	(7.816)	
Order-date volatility		-3.423
		(6.975)
1(CoP volatility<Order-date volatility)		0.008**
		(0.002)
Log(Term Length)	0.000	0.000
	(0.001)	(0.001)
Log(Premium)	0.005**	0.005**
	(0.001)	(0.001)
Self	0.039**	0.039**
	(0.002)	(0.002)
Female	0.006**	0.006**
	(0.001)	(0.001)
Adj. R-squared	0.008	0.008
Observations	353,924	353,924

Notes: For each column, the dependent variable is whether an insurance contract is canceled during the cooling-off period. All coefficients represent the marginal effects from a probit regression. *Relative volatility* is the average volatility during the cooling off period minus the order date volatility. All regressions included controls for day of week, week of year, year and city. Standard errors are clustered on city*date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

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