Fear: Endogenous Risk Aversion, Stock Market Volatility, and Financial Decision-Making

Tom Y. Chang*, Wei Huang, Hui Lin, and Yongxiang Wang†

December 7, 2020

ABSTRACT

Using data from a large commercial bank and a large retail insurance company, we examine the impact of the stock market volatility on financial decision-making. Consistent with prior experimental evidence that stock market volatility increases individual risk aversion, we find that on days with high stock market volatility, individuals purchase more life insurance and loan officers set a higher hurdle rate for loan approval.

*Corresponding author: Tom Y. Chang, 701 Exposition Boulevard, Ste. 231, Los Angeles, CA, 90089-1422, email: tychang@marshall.usc.edu, phone: 213-740-1135, fax: 213-740-6650

†Chang and Wang are at the University of Southern California. Huang is at the University of International Business and Economics. Lin is at Nanjing University. We are grateful to Harry DeAngelo, Cary Frydman, Ori Heffetz, Mireille Jacobson, Lawrence Jin, George Loewenstein, Terrance Odean, Anya Samek, Joshua Schwartzstein and seminar participants at Berlin Behavioral and Experimental Seminar, Hong Kong Polytechnic University, Hong Kong University of Science and Technology and the University of Southern California for helpful discussions and comments. An earlier version of this paper circulated under the title "Reverse Animal Spirits."

1 Introduction

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). In the realm of behavioral asset pricing, empirical work has focused almost exclusively on how the psychology of investors affects markets (see Baker and Wurgler (2007) for a review). Theory, on the other hand, posits the existence, and importance of the reverse effect - markets affecting the psychology of investors - and thus the existence of feedback loops that can have important economy-wide consequences (Shiller (2000)). In this paper, we attempt to help fill that gap by examining how both consumers and financial professionals respond to stock market fluctuations. Specifically, following the work of Lo and Repin (2002), we test whether high-frequency stock market volatility leads to fear-induced risk aversion. Consistent with the hypothesis, we find that daily stock market volatility has a significant effect on both the demand for life insurance and the decision-making of loan officers.

Using policy level data from a large Chinese insurance company, we examine the relationship between the performance of the Shanghai stock index and the demand for life insurance policies.[1] We find that a one standard deviation increase in daily stock market volatility is associated with a 2.5% increase in the number of life insurance policies sold that day. In contrast, daily stock market returns do not appear to have a meaningful effect on the demand for insurance. We also find that contracts are more likely to be canceled if stock market volatility decreases during the 10-day government-mandated cooling-off pe-

[1]Several factors make China a good environment to test whether stock market performance can affect decision-making. First, in China, stock market participation is 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. In such an environment, stock market conditions are likely to be salient to both potential buyers of insurance products and bank loan officers.

riod, during which individuals can cancel their newly purchased insurance policies at no cost. 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.

Next using loan level data from a large Chinese bank, we examine the relationship between daily stock market volatility and the decision by loan officers to approve commercial loan applications.[2] We find that increases in daily price volatility lead loan officers to approve fewer loans, and that these loans appear safer ex-ante and perform better ex-post. As with the demand for health insurance, daily stock market returns do not have a significant effect on loan officer decision-making. The coefficients for lagged measures of market volatility are smaller in magnitude and statistically insignificant, suggesting that the effect is both immediate and short lived.

We explore and reject the idea that the change in behavior we document is the result of information relevant to the decision to purchase life insurance or approve commercial loans associated with high market volatility. First, we find that a single day's market volatility contains very little additional information about future market conditions even in the short run. As such, it is highly unlikely that they contain enough information about the future credit worthiness of commercial borrowers or an individual's life expectancy (or future wealth) to generate the effect sizes we observe. Second, the impact of volatility on both the demand for insurance and the behavior of loan officers is robust to excluding days with high levels of market volatility. Since days with large market swings are more associated with new and long-lasting information, this result indicates that the effect we document is not driven by information or learning.

Taken together, these results provide strong evidence that daily stock market conditions

[2]Due to institutional features of the bank, the set of loan applications reviewed on any given day are as-if randomly assigned with respect to contemporaneous stock-market conditions. As such, changes in loan-officer behavior can plausibly be attributed to contemporaneous changes in stock market conditions.

affect long-term financial decision-making via psychological factors. To the best of our knowledge, ours is also the first direct evidence that shows stock market conditions affect financial decision-making of financial professionals outside of the lab.

Our paper builds upon a small literature that examines the psychological impact of market performance on individuals in laboratory settings. Lo and Repin (2002) study the responses of 10 experienced traders to contemporaneous market conditions and 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 also 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 from the field that financial market conditions can have a psychological effect on individual risk aversion. Our findings, that normal market conditions can generate meaningful fluctuations in aggregate risk aversion, complement their results by extending the domain of such emotionally induced fluctuations from major financial crises, to the everyday.

Indeed, a key difference between our findings and those of both Cohn, et al. (2015)

and Guiso et al. (2018), who find that financial disasters increase investor risk aversion, is that our results are driven not by extreme events, but rather by the normal, day-to-day variation in stock market conditions. This finding suggests that feedback from investors to the markets and from markets back to investors is potentially an important feature of day-to-day market conditions, rather than something that matters only for more extreme events like price bubbles and crashes. In this way, our paper is most similar to Engelberg and Parsons (2016), who use a similar methodology 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." Unlike Engelberg and Parsons (2016), who attribute their findings to expected wealth effects associated with stock market returns, we find little evidence that returns, or information more generally, affect individual behavior. Rather we find evidence for a psychological channel through which market volatility affects individual behavior. To the extent that our results are generalizable outside of our setting, they suggest that investor's psychological responses to markets are a potential mechanism behind several puzzles in finance including the equity premium puzzle and excess market volatility.

Finally, our result on the effect of contemporaneous conditions on decision-making is related to work in behavioral economics on the oversized effect of current conditions on long-run decision-making. Consistent with both projection bias and salience, Conlin, O'Donoghue and Vogelsang (2007), Busse, Pope, Pope and Silva-Risso (2014) and Chang, Huang and Wang (2018) show that idiosyncratic variation in environmental conditions affects the demand for cold-weather items, automobiles, and health insurance respectively.

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

2 Data

As our measure of stock market performance, we use 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 daily market volatility, but as shown in specification checks, the results are robust to the use of alternative measures of daily volatility.

Our insurance data are from a large Chinese insurance company and includes contract level information for all life insurance policies 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. Typical of the life insurance market in China in general, close to 100% of life insurance policies sold are guaranteed issue whole life policies, and thus do not involve either a medical exam or waiting 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 purchaser or a family member, and cancellation information. Of these, dropping sales on days on which the Shanghai Stock Market was closed leaves us with a sample of 353,924 insurance contracts over 8,729 days. Chinese regulations allow individuals to cancel their insurance purchase at no cost during a 10-day cooling-off period, and such cancellations take place in approximately 9.1% of the contacts in our sample.

Our loan data is from a large Chinese bank. Our sample includes detailed loan level information for a randomly selected 10% subset of all commercial loans made by the bank from 2006 through 2010. 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 loan or firm characteristics.

In addition to not being able to share details about loan and firm characteristics in the paper, the loan 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 does not record the date when the initial loan is approved, but rather when the loan is funded (i.e., when 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 loan portfolio, and provide us with a sample of 40,808 loans.

While most 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.

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

[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.

may originate from any office, in an effort to combat corruption, in 2005 the bank, like other large 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 applications to individual loan officers for review. There is no hard and fast rule (e.g., FIFO) regarding the receipt of a loan application and assignment for review, but in conversations with the bank we were informed that 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.

Our measure of loan performance is based on the Peoples Bank of China's official classification system as described in the "Guiding Principles for Loan Classification" (PBOC 1999). Issued by the central government in 1999, the PBOC requires 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 repay 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"[4] by Chinese bank regulators. Our baseline specification classifies only loans

[4] Bu Liang Dai Kuan in Chinese.

in default (i.e., Doubtful and Loss loans) as distressed. In robustness checks, we include loans classified as Substandard as being in distress, as well as treating only loans classified as Loss as in distress. Approximately 4% of the loans in our sample are classified as Loss, 4% as Doubtful, and 2% as Substandard.

3 Market Volatility and the Demand for Insurance

We first examine the relationship between market volatility and risk aversion by examining the relationship between daily stock market performance and the product most closely tied to risk aversion: insurance. Specifically, we analyze the relationship between daily stock market volatility and the number of life insurance policies sold that day. Importantly, because the price and other characteristics for the product we examine vary infrequently during our sample period, changes daily sales can plausibly be associated with changes in aggregate demand for insurance. Thus, if higher levels of stock market volatility cause individuals to be more risk adverse, we should see a positive relationship between the demand for life insurance and stock market volatility.

We test for this relationship by estimating the following regression for all trading days between January 1, 2011 and December 31, 2014:

$$Log(Policies\ Sold)_{jt} = \beta Return_t + \nu Volatility_t + city_j + D_{jt} + \epsilon_{jt}, \tag{1}$$

where $Log(Policies\ Sold)_{jt}$ is the log of the number of insurance policies sold in city j on date t, $Return_t$ is the daily return of the SSECI in percentage terms on date t, $Volatility_t$ is a measure of the daily volatility of the SSECI on date t, $city_j$ are city fixed effects, and D_{jt} are day-of-week, week-of-year, and year fixed effects, included to account for possible seasonal variation in insurance demand. The main coefficients of interest are β

and ν, which capture the effect of daily stock market return and volatility on the number of contemporaneously sold life insurance policies. Daily returns are calculated as the difference between the market close and market open divided by market open, while daily volatility is the square of daily returns. In robustness checks, we also use the measures of daily volatility described in Parkinson (1980) and Rogers and Satchell (1991). Standard errors are clustered on city and date.

The results of this analysis are shown in Table 1. Columns 1 and 2 calculates the effect of daily stock market conditions on same-day insurance sales using OLS and Poisson regressions, respectively. Column 3 and 4 repeat this analysis, but uses the 2-day average volatility as the measure of concurrent volatility. This latter specification helps to account for the fact that there can be a lag between the decision to purchase insurance and the actual purchase. In all cases, the results show that daily stock market volatility has a strong, positive impact on demand for insurance across China. The coefficient from column 1 indicating that a one standard deviation increase in average daily volatility is associated with a 2.5% increase in daily insurance contracts sold.

3.1 Robustness

We next examine the robustness of our main results to different measures of daily volatility and date fixed effects. In columns 1 and 2 of Table 2, we replace the simple measure of daily volatility with those described in Parkinson (1980) and Rogers and Satchell (1991) respectively. The coefficients on volatility remain positive and significant, and when scaled by variance, leads to point estimates of similar magnitudes to Table 1, column 1.

In columns 3-5 of Table 2, we address the possible issue of seasonality driving these results by rerunning the regression from Table 1 column 1 but replace the year and week-of-year fixed effects with different sets of time fixed effects: column 3 year and month, column 4 month-by-year, column 5 week-by-year. While the magnitude of the coefficient decreases for some of the more aggressive specifications, in all cases, the coefficient of volatility remain positive and statistically significant.

3.2 Learning

While these results are consistent with volatility induced risk aversion, they do not exclude other alternative mechanisms. Perhaps the most obvious explanation for these results is that daily volatility is associated with novel information to potential insurance customers that changes the calculus of their decision-making. For example, to the extent that life insurance is thought of as a financial asset, if increased daily stock market volatility signals persistently higher future volatility, increased demand for life insurance may simply be rational rebalancing of portfolios towards safer assets.

To test whether daily stock market conditions have predictive power regarding future stock market performance, we run the regression

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

where $Cumulative\ Return_{t,\tau}$ is the percentage return of the Shanghai Stock Market over the period $\tau \in \{$*Week, Month, Quarter, Half-Year,* $\}$ starting on date t, $Return_t$ is the percent return of the SSECI on date t, $Volatility_t$ is a measure of the daily 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 panel A of Table 3. They show that while daily returns have predictive power on cumulative returns for up to one quarter into the future, daily volatility is uncorrelated with cumulative returns across any of the time periods we examine. As such, these results indicate that daily volatility does not, on average, contain much information about the subsequent performance of market beyond a relatively short time horizon. Panel B of Table 3 shows the results of repeating this regression with future volatility as the dependent variable. As before, the coefficient for daily volatility is small and statistically insignificant in all four columns, indicating that daily market volatility does not predict future market volatility across all four of our time horizons.

While these results are not surprising, they do confirm that during our study period, daily stock market volatility did not provide investors with much marginal information about future market conditions, even in the short term. Since life insurance policies are medium to long term investments, these results provide evidence against the idea that there is sufficient marginal information in a day's market volatility to lead to such a large increase in demand.

Moreover, given these results, if changes in individual decision-making was due to new information, one would expect returns, and not volatility, to have an effect on the demand for life insurance. This is indeed the pattern of results found in Engelberg and Parsons, who find that individuals respond to informative daily returns, and not volatility. In this case however, we find the opposite with the demand for life insurance significantly affected by market volatility, and not returns.

While these results indicate that on average, daily market conditions do not include significant amounts of information about the long run performance of the stock market, there may be certain days (e.g., market crashes, important earnings announcement days) that do contain significant amount of information. As such, one potential concern is that our results may be driven by such extreme, informative days. To test this hypothesis, we explore the sensitivity of our results to days with unusually high levels of daily market volatility or changes in market value. Since such extreme days are much more likely to be days on which the market learns significant new information, if the relationship between life insurance demand and market volatility is due to learning, then the effect should be attenuated when such days are excluded.

To test this prediction, we rerun our main regression specification excluding days that correspond to the largest 1% and 5% of daily market volatility.[5]. The results of this analysis are presented in Table 4. Column 1 of Table 4, which corresponds to dropping 1% of the sample, generates very similar magnitude coefficients to the main regression. Column 2, in which we exclude 5% of the highest volatility days, the coefficient for volatility actually increases in magnitude by nearly half. Together, these results indicate that the effect we find is not driven by extreme days, but is rather a feature of "ordinary" day-to-day variation in volatility.

Taken together, the lack of predictive power of a single day's market performance and the lack of attenuation when extreme days are excluded from the sample, provide strong evidence against the idea that the behaviors we document are the result of rational learning on the part of potential insurance buyers.

3.3 Supply Side Response

Another potential concern is that our findings are driven, or at least biased, by changes in the behavior of the insurance company in response to stock market volatility. For example, if the insurance company could change prices in a way correlated with stock market volatility. If so, such changes could have a material effect on the relationship between daily stock market volatility and sales. The two main concerns in this instance are that the firm change the features of their insurance policies (e.g., price) or changes efforts related to marketing and sales. Fortunately, these concerns are largely mitigated by the high frequency (daily) nature of our data and institutional features of the life insurance market in China.

Importantly, for our analysis, product characteristics, including prices, are set at the

[5] Note that under our preferred daily volatility measure, this is equivalent to dropping days corresponding to the largest absolute changes in market returns.

company level and vary infrequently. Marketing and advertising are also unlikely to be a factor as they do not vary at anything approaching the frequency required to affect our regression results. One possibility source of supply side variation that could occur at the daily level is the effort level of the sales staff. For example, high stock market volatility might induce sales agents to put forth more effort into selling life insurance. While we cannot directly rule out this possibility, we note that given our rejection of an informational channel, it would imply that market volatility has a psychological effect on sales agents.

3.4 Cancellations

In order to more directly test whether the relationship between stock market volatility and insurance sales is due to psychological factors, we next examine the effect of daily stock market volatility on insurance cancellations. If individuals were induced to buy insurance due to contemporaneous psychological factors associated with 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 for projection bias used in Conlin, O'Donoghue and Vogelsang (2007), Busse et al. (2012), Chang, Huang, and Wang 2018). Significantly, such a pattern of cancellations makes it even less likely that the documented changes are driven by non-psychological factors (see Loewenstein, O'Donoghue and Rabin (2003)).

Following Chang, Huang and Wang (2018), we examine the relationship between stock market volatility and cancellations using the following regression specification:

$$Cancel_{ijt} = f(volatility_t, ..., volatility_{t+11})\beta + C_{ijt}\gamma + D_{jt} + \epsilon_{jt}, \tag{3}$$

where $Cancel_{ijt}$ is a dummy variable that equals 1 if contract i purchased in in city j on date t cancels an insurance contract within 11 days of purchase.[6] $volatility_t$ is daily stock market volatility on date t, and ($volatility_{t+1,\ldots,t+11}$) 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 and 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 when the purchase decision is made and when the cancellation decision 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

$$Cancel_{ijt} = \beta(Relative\ volatility_t) + C_{ijt}\gamma + D_{jt} + \epsilon_{jt}, \tag{4}$$

where

$$Relative\ volatility_{ijt} = \sum_{\tau=1}^{11} \frac{1}{11}(volatility_{ij,t+\tau} - volatility_{ijt}). \tag{5}$$

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 and a dummy variable that indicates whether the average stock market volatility during

[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.

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 3, column 1 presents the regression result of the impact of 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 an 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. Notably, 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 on 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.

These results show that the demand for insurance is positively correlated with stock market volatility, leading to more sales on high-volatility days and more cancellations when stock market volatility decreases immediately after purchase.

4 Market Volatility and Commercial Loan Approval

We next examine the relationship between stock market performance and the behavior of loan officers. Specifically, we examine the relationship between loans approved on a given day with that day's stock market conditions. If, as hypothesized, market volatility causes loan officers to be more risk adverse, the hurdle rate for approval should increase. As such, we would expect to see a specific pattern of results: loan officers should approve fewer, higher quality loans on days with high stock market volatility.

As discussed in the data section, a key limitation of data is that we do not have data on rejected loans. As such, our identification strategy relies on the portfolio of loans reviewed by the bank on any given day being unrelated to that day's market conditions. If the portfolio of loans reviewed on a given day is unrelated to that day's market conditions, any difference in approved loans is plausibly caused by changes in loan officer decision-making due to the contemporaneous market conditions.

One key potential threat to our identification strategy would be if contemporaneous market conditions affect the timing of when a firm applies for a loan extension. This channel is quite 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 a significant lag (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 to coincide with specific market conditions would not only have to accurately predict 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 choose to put off reviewing difficult to assess applications on days with significant stock market volatility. This concern is 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 officers 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 since loan applications assignments are made at the start of the bank's workday at 8.30 AM before the open of the Shanghai Stock Exchange at 9.30 AM.[7] Moreover, since managers are unlikely to carefully review loan applications before assignment, their ability to discriminate across loan applications is limited. In addition, as discussed below, the relationship between stock market volatility and the quantity and quality of approved loans is stronger when we exclude days with high volatility. To the extent that large changes in the market are easier to ex-ante predict shortly before the market open, this finding provides some evidence against the effects we document being driven by biased assignment of loan applications by prescient managers.

4.1 Volatility and Loan Quality

One of the two main predictions of volatility induced risk aversion for loan officers is that the quality of the loans approved should increase on days with higher stock market volatility. In this section we test this prediction using several measures of loan quality. As our primary measure of loan quality, we use ex-post loan performance. Specifically, we code a dummy variable *Distress* equal to 1 if the bank classifies the loan as having an expected loss rate of over 50%.

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

Figure 1a plots the relationship between daily returns of the SSECI and the share of contemporaneously approved loans that are categorized as non-performing by 1 basis point bins. The figure shows a striking symmetric relationship between market returns and the performance of contemporaneously approved loans, with the probability of loan distress decreasing with both daily gains and losses. That is, loans approved on days on which the market experience large gains or losses are less likely to end up in default.

Figure 1b plots the relationship between the intraday volatility of the SSECI and the subsequent share of contemporaneously approved loans by bins. Consistent with figure 1a, figure 1b shows a clear negative relationship between volatility and loan performance in the raw data. That is the share of non-performing loans decreases with daily volatility.

While these figures provide evidence of the negative relationship between daily volatility and the ex-post performance of contemporaneously approved loans, to help rule out the possibility that the relationship is due to other factors (e.g., seasonality in the quality of loans and stock market volatility), we next subject the relationship to regression analysis. Our baseline specification for estimating the impact of stock market on the subsequent performance of loan extensions is given by the following equation:

$$Distress_i = \beta Volatility_t + \nu Return_t + X_{it}\gamma + D_t + \epsilon_{it}, \tag{6}$$

where $Distress_i$ is a dummy variable equal to 1 if a commercial loan i granted an extension 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 daily 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 and day-of-week variation in loan applications. Standard errors are 2-way clustered on date and region. The main coefficients of interest are β and ν, which capture the effect of stock market returns and volatility on the subsequent performance of contemporaneously approved loan extensions.

The results of estimating Equation 6 are presented in Table 6, and show a pattern of results consistent with the visually apparent pattern in figures 1 and 2. Column 1 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 β indicates that a one standard deviation increase in daily market volatility is associated with an 3.4% decrease in the probability the loan becomes distressed. Column 2 examines the impact of daily returns on subsequent loan performance. In contrast to column 1, the point estimate for ν is small and statistically insignificant. Column 3 shows the results of a regression that includes both daily return and volatility, and finds very similar point estimates to regressing each factor independently.

Column 4 looks at the effect of leads and lags of market conditions on loan performance. In the case of loan applications, since we know the day on which a loan is reviewed, a significant coefficient on lagged market conditions would indicate that daily market conditions affect decision-making on subsequent days. Column 4 reruns the regression shown in column 3 but includes leads and lags for both volatility and returns. Including leads and lags have virtually no effect on the magnitude of either coefficient, and the coefficients for the lead and lag for market volatility are small and statistically insignificant. The results on lagged market conditions indicate that the effects of market volatility on decision-making are immediate and do not carry over into subsequent days. The results on lead market conditions indicates that individuals are either unable to predict the next day's market volatility, or to the extent that they can, that it does not affect their decision-making. The null results on leads and lags also serve as a placebo tests, providing evidence for the validity of our identification strategy.

4.1.1 Robustness

In Table 7, we present the results of various robustness checks on the results presented in Table IV. 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 daily 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. As with the results for insurance demand, 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 baseline 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 baseline 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 scheduled payments, but are thought by the bank to be in significant danger of future default. The point estimate is very similar to that of the baseline specification, and statistically significant. In column 4, we exclude loans that are in default, but for which the bank expects a loss rate of less than 75%. Using this highly restrictive definition of financial distress decreases the size of the coefficients of interest by half, and coefficient is no longer statistically significant. This result is likely the result of a reduction of statistical power, and not due to de

Finally, we attempt to mitigate the concern that our included time controls do not adequately account for seasonal variation. The results of Table IV, 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 V, we repeat our main analysis using seasonal controls both coarser and finer than the one used in our main regression specification: year and month fixed effects (column 5), month-by-year fixed effect (column 6), week-by-year fixed effects (column 7). Across all specifications, we find a strong and statistically significant negative relationship between daily market volatility and the probability that a contemporaneously approved loan eventually defaults.

4.1.2 Ex-Ante Loan Characteristics

We next explore the impact of market volatility on loan quality by examining the characteristics of borrowers. While loan performance is perhaps the most straightforward measure of ex-post loan quality, borrower characteristics provide one measures of ex-ante loan quality. For example, loans to companies with better credit ratings, all else equal, are ex-ante should be less likely to fail than those made to companies with worse credit ratings.

Table 9 presents the results of rerunning our basic regression with borrower and loan characteristics as the dependent variable. Columns 1-3 show that daily market volatility is associated with approved loans being made to companies with higher credit ratings, lower leverage, and are of higher value. Furthermore, loans approved on days with high stock market volatility also tend to be made to larger firms (column 4), and firms not owned by the state (column 5), though in neither of these two cases is the relationship statistically significant. These results indicate that loans approved on days with high stock market volatility appear to be safer ex-ante and perform better ex-post.

Consistent with the results on loan performance, and in contrast to daily market volatility, we find that daily market returns have no measurable impact on these characteristics, with the coefficient for market returns small in magnitude, and statistically insignificant at conventional levels across all columns of Table 9.

4.2 Volatility and Loan Quantity

The other key prediction of volatility induced risk aversion was that fewer loans should be approved on days with high stock market volatility, and this decrease should be driven by higher rejection rates of marginal loans. Because we do not have data on the set of rejected loans, we examine the relationship between the number of loans approved on a given day and stock market performance. Under the assumption that the portfolio of loans reviewed on a given day is unrelated to volatility, differences in the absolute number of approved loans can be attributed to the behavior of loan officers.

We first examine the relationship between daily SSECI volatility and the number of contemporaneously approved loans graphically. Figure 2a plots the relationship between daily returns of the SSECI and the share of contemporaneously approved loans that are categorized as non-performing by 1 basis point bins. As with loan performance, we see across both panels a negative relationship between the absolute value of market returns and the number of loans approved.

Figure 2b plots the relationship between the intraday volatility of the SSECI and the number of contemporaneously approved loans by bin, and consistent with figure 2a, shows a negative relationship between volatility and the number of contemporaneously approved loans. That is the bank approves fewer loans on days with higher levels of market volatility.

We next examine the relationship between the number of loans approved and stock market volatility using the following regression:

$$Loans_t = \beta Return_t + \nu Volatility_t + D_t + \epsilon_{it}, \tag{7}$$

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 daily volatility on date t, and D_t are day-of-week, week-of-year, and year fixed effects.

Table VII 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 approved loans. Consistent with the prediction of volatility induced risk aversion, Column 1 indicates that higher stock market volatility is associated with decrease in the number of approved loans. When we restrict the data to the number of loans that eventually default (column 2), the coefficient for daily volatility increases by a factor of 6. In contrast, when the data is restricted to loans that do not default (column 3), the coefficient for volatility decreases relative to the full sample. This indicates that the decrease in the number of approved loans is not random, but rather driven by the loans on the margin of approval - precisely what one would expect if loan officer's risk aversion increases on days with higher stock market volatility.

Unlike the previous results on loan performance and the demand for life insurance, market returns appear to have a small, but statistically significant impact on the contemporaneous number of loans approved (column 1). Unlike market volatility, this effect is driven by loans that do not enter default (column 3).

Overall, these results confirm the second key prediction of volatility induced risk aversion: loan officers approve fewer loans on risker days, and the decrease in loan approvals is driven by loan officers reject marginal loans that they would have approved on days with low levels of stock market volatility.

5 Alternate Mechanisms

Our main empirical findings are that daily market volatility causes loan officers to be more conservative in approving loans. While these results are consistent with the idea that market volatility increases the risk aversion of both consumers and loan officers, they are not dispositive. As such, in this section, we explore possible alternative explanations for our findings.

5.1 Learning

As with life insurance, one possible explanation for these results is learning, broadly defined. That is that the change in behavior by loan officers is a rational response to information contained in, or associated with, daily stock market volatility. For example, high daily volatility might predict higher levels of economic volatility in the future, in which could increase the riskiness of some commercial loans.

This concern is largely mitigated by the fact that a single day's market volatility tends to contain very little information. That is as shown in the previous section, current stock market volatility is not a predictor of future market conditions over even short time horizons (Table 3). As such, it is hard to imagine that a single day's stock market volatility provides a meaningful amount of information about the riskiness of commercial loans.

We supplement this general result by examining the sensitivity of loan performance to excluding days in which the market experiences extreme swings in either direction. To the extent that such extreme days are much more likely to be days on which the market learns significant new information, if the relationship is due to learning, then the effect should attenuated when such days are excluded. To see if such days are driving our results, in columns 1 and 2 of Table 8, we rerun our main regression specification excluding days that correspond to the largest 1% and 5% swings in daily gains and losses. In both cases, the coefficient for daily volatility remains statistically significant with point estimates that are actually larger in magnitude than in the baseline case. 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.

In the case of loans, future performance of the loans provides an additional way to differentiate between volatility induced risk aversion and learning. Specifically, while changes in risk aversion changes the hurdle rate for loan approval, informative signals about future market conditions should have no impact on the hurdle rate. Rather, changes in future market conditions should instead change the composition of firms above and below a stable cutoff for loan approval. As such, if the change in loan officer behavior is driven by informative signals about loan performance, then the change should be limited to the number of loans approved, and no the subsequent performance of approved loans. Instead, we find that, consistent with an increase in the hurdle rate, loans approved on high volatility days perform significantly better than those approved on low volatility days.

5.2 Decrease in Effort

Another possible explanation for our findings is that market volatility serves as a distraction, decreasing the time available for other activities. For example, perhaps loan officers spend so much time and energy thinking or engaging in trading on high volatility days that they spend less time and effort evaluating loan applications.

There are several reasons to think that such reductions in effort are not driving our results. Table IV indicates that higher market volatility leads loan officers to essentially make better decisions (i.e., reject bad loans), which can be considered prima-fascia evidence against the distraction hypothesis. That is, distraction should lead to worse decision-making, not better.[8] However, in theory, decreased overall efforts could lead to better outcomes. For example, if loan officers mistakenly have too low of a hurdle rate, then if when pressed for time these over-optimistic loan officers reject marginal loans because they require higher levels of effort to evaluate. Such a scenario could then lead to a de-facto increase in the hurdle rate.

One test for the distraction hypothesis is to look for a relationship between the size of

[8]While we do not have direct evidence that the rejected loans were unprofitable for the bank, it seems quite unlikely that a loan that defaults within a few years with an expected loss rate of greater than 75% would be something a bank would want.

the distraction and the effect sizes we document. Specifically, to the extent that one would assume workers are most distracted on extremely high volatility days, we would expect to see larger effect on precisely those dates. Instead, as shown in Table 8, we find no evidence of such increasing effect sizes. Rather, if anything, we find some suggestive evidence that the effect size actually decreases on precisely those days when we would expect the loan officers to be the most distracted.

Perhaps the strongest evidence against the reduced effort hypothesis though is effect of market volatility on the demand for insurance. Specifically, to be consistent with both sets of results, market volatility would need to induce opposite behaviors among potential buyers of life insurance and loan officers. Specifically, since it takes positive effort to buy insurance, if market volatility distracts individuals, then it should lead to a decrease, and not increase, in the demand for insurance policies. These arguments though are far from dispositive, and illustrate in part the difficulty in differentiating between changes in risk aversion and other psychological changes to the decision-making process more generally.

6 Conclusion

Our main empirical findings are that daily stock market volatility affects financial decision-making far out of proportion to any potential informational content but consistent with volatility induced risk-aversion. On the consumer side, we find that individuals demand more insurance on days with high stock market volatility, and conditional on purchase, decreases in market volatility relative to the purchase-date levels lead to an increase in the cancellation rate. Among financial professionals, we find that loan officers appear to be more conservative when approving loans when stock market volatility is high. Loans approved on days with high volatility are associated with both lower ex-post default rates and appear safer ex-ante. This increase in average loan quality is driven by a decrease in the number of marginal loans.

These results suggest that visceral responses to uninformative environmental factors can have an economically meaningful effect on long-run financial decision-making by both individuals (life insurance) and firms (loans). Specifically, that the “significant emotional response” to price volatility documented by Lo and Repin (2002) in the lab, occurs in the field, even among financial professions. These results also 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 Engelmann, Fehr and Marechal (2015) and Guiso, Sapienza and Zingales (2018).

As such, our paper provides evidence of an important psychological channel through which the stock market meaningfully affects the real economy. Significantly, our results suggest that ordinary day-to-day variation in stock market performance can cause changes in risk-aversion, even among financial professionals. That is, while the stock market is not the real economy, it 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 historical data (Campbell and Cochrane (1999)).

References

Baker, M., and J. Wurgler (2007). "Investor Sentiment in the Stock Market," *Journal of Economic Perspectives*, 21 (2): 129-152.

Busse, M., J. Pope, D. Pope, and J. Silva-Risso (2015). "The Psychological Effects of Weather on Car Purchases," *Quarterly Journal of Economics*, 130(1): 371-414.

Conlin, M., T. O'Donoghue, and T. Vogelsang, (2007). "Projection Bias in Catalog Orders," *American Economic Review*, 97(4): 1217-1249.

Campbell, J., and J. Cochrane (1999). "By force of habit: a consumption-based explanation of aggregate stock market behavior," *Journal of Political Economy*, 107 (2): 205-251.

Cohn, A., J. Engelmann, E. Fehr, and M. Marechal (2015). "Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals," *American Economic Review*, 105 (2): 860-885.

Chang, T., W. Huang, and Y. Wang (2018). "Something in the Air: Pollution and the Demand for Health Insurance," *Review of Economic Studies*, 85 (3).

DellaVigna, S. (2009). "Psychology and Economics: Evidence from the Field," *Journal of Economic Literature*, 47, 315-372.

Engelberg, J., and C. Parsons (2016). "Worrying about the Stock Market: Evidence from Hospital Admissions," *Journal of Finance*, 71 (3): 1227-1250.

Guiso, L., P. Sapienza, and L. Zingales (2018). "Time varying risk aversion," *Journal of Financial Economics*, 128 (3): 403-421.

Keynes, J. M., (1936). *The General Theory of Employment, Interest and Money*, London: Palgrave Macmillan.

Lo, A., and D. Repin (2002). "The Psychophysiology of Real-Time Financial Risk Processing," *Journal of Cognitive Neuroscience*, 14 (3): 323-339.

Loewenstein, G. (2000). "Emotions in Economic Theory and Economic Behavior," *American Economic Review*, 90 (2): 426-432.

Loewenstein, G., T. O'Donoghue, and M. Rabin (2003). "Projection Bias in Predicting Future Utility," *Quarterly Journal of Economics*, 118, 1209-1248.

Parkinson, M. (1980). "The Extreme Value Method for Estimating the Variance of the Rate of Return," *Journal of Business*, 53, 61?65.

People's Bank of China (1999). "Guideline on Risk-based Loan Classification."

Rogers, L. and S. Satchell (1991). "Estimating Variance from High, Low and Closing Prices," *Annals of Applied Probability*, 1, 504-512.

Paravisini, D. and A. Schoar (2016). "The Incentive Effect of Scores: Randomized Evidence from Credit Committees," *NBER Working Paper No. 19303*.

Shiller, R. (2000). *Irrational Exuberance*," Princeton N.J., Princeton University Press

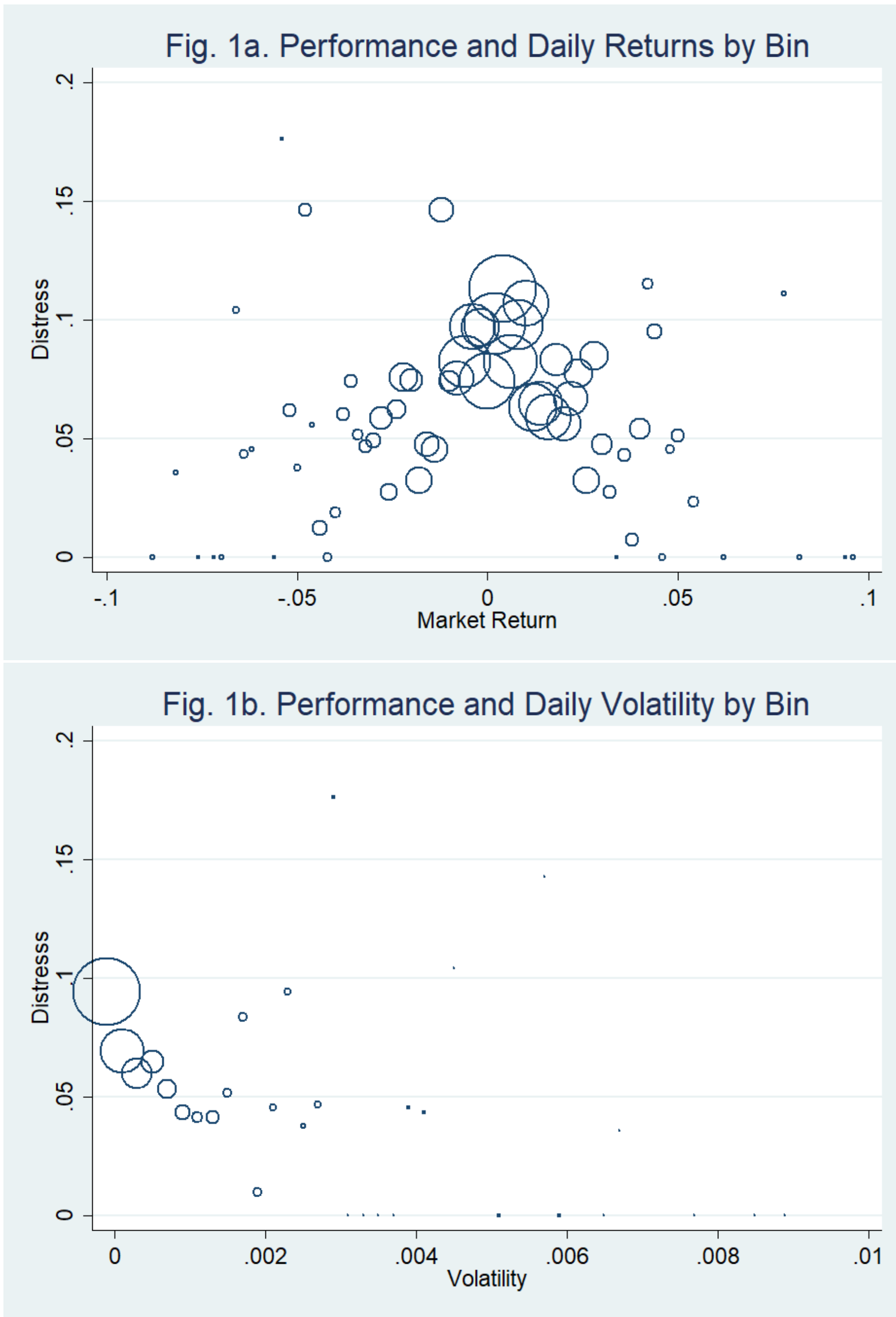
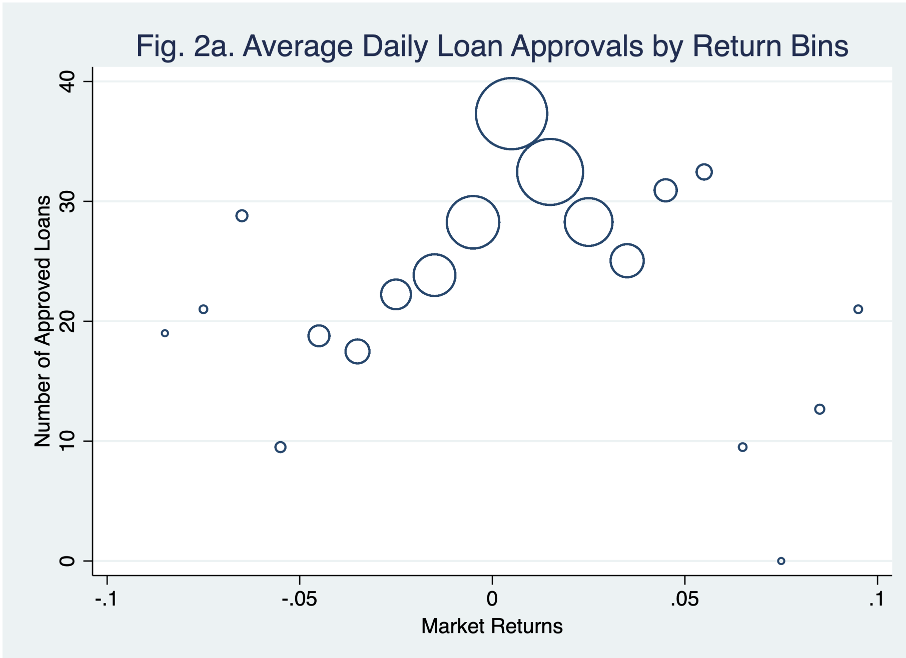


Figure 1. Loan Distress Rates and Daily Stock Market Conditions
Note: size of the circle represents the number of loans in each bin.



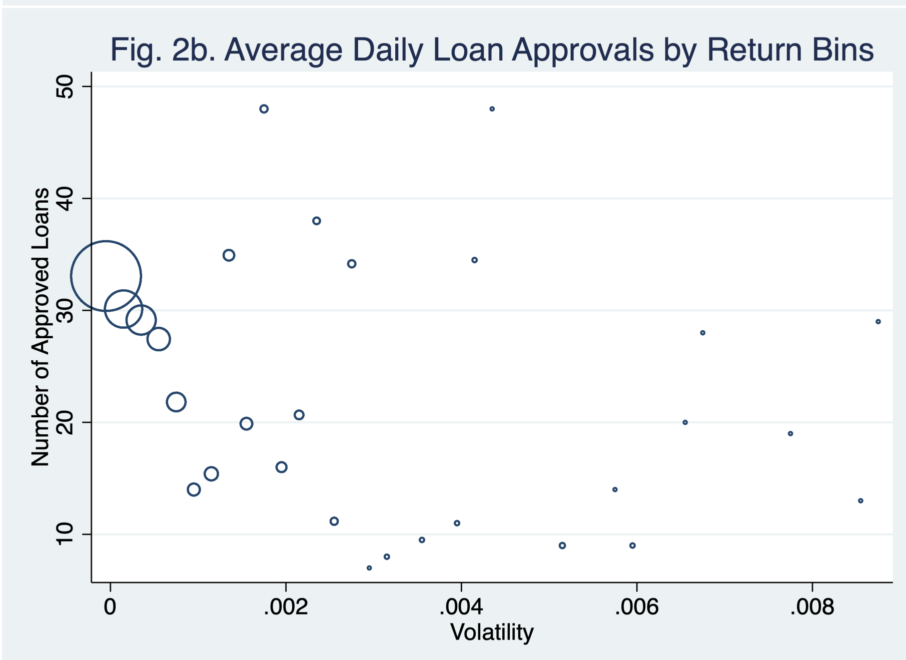


Figure 2. Number of Approved Loans and Daily Stock Market Conditions
Note: size of the circle represents the number of days in each bin.

Table I
Demand for Insurance

	(1)	(2)	(3)	(4)
Volatility	99.708**	108.916**	179.316**	182.746**
	(29.999)	(29.456)	(49.962)	(40.928)
Returns	-0.4299	-0.4243	-0.6059	-0.5981
	(0.5828)	(0.6377)	(0.5924)	(0.6395)
R-squared	0.6620	0.6319	0.6622	0.6323
Observations	8,729	8,729	8,729	8,729

Notes: Columns 1 and 3 show the results of OLS regressions with the log of the total number of life insurance policies sold on a given day in a given city. Columns 2 and 4 show the results of Poisson regressions on the total number of insurance policies sold on a given day in a given city. Columns 1 and 2 uses volatility on the date of purchase, while column 3 and 4 use the average volatility on the date of, and the date before, purchase. All regressions included controls for city, day-of-week, week-of-year and year. OLS standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table II
Demand for Insurance Robustness

	Volatility Measures		Date Fixed Effects		
	(1)	(2)	(3)	(4)	(5)
Volatility	2.9890**	5.3114**	91.2369**	31.0639*	34.3005*
	(1.0428)	(1.7143)	(37.4246)	(14.0754)	(13.7064)
Return	-0.6504	-2.1538	-0.5057	-0.4754	-0.2802
	(0.5903)	(1.4412)	(0.7088)	(0.5432)	(0.4675)
R-squared	0.6621	0.6622	0.6495	0.6660	0.6902
Observations	8,729	8,729	8,729	8,729	8,729

Notes: The dependent variable is the log of the total number of life insurance policies sold on a given day. Columns (1) and (2) use the volatility measures described in Parkinson (1980) and Rogers and Satchell (1991) respectively. . Columns (3), (4), and (5) replace the week-of-year and year fixed effects with month and year, month by year, and week by year fixed effects, respectively. All regressions included controls for city, day-of-week, week-of-year and year. Standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table III
Daily Marginal Information

Panel A: Percent Cumulative Return

	One Week	One Month	One Quarter	Half Year
	(1)	(2)	(3)	(4)
Volatility	4.1689*	0.4976	3.4289	-1.3517
	(1.6748)	(3.2075)	(4.7143)	(6.4530)
Return	0.8210**	0.6400**	0.4304*	0.4590
	(0.0610)	(0.1280)	(0.2065)	(0.2872)
Adjusted R-squared	0.3392	0.4434	0.6646	0.7370
Observations	1,126	1,116	1,087	1,022

Panel B: Volatility

	One Week	One Month	One Quarter	Half Year
	(1)	(2)	(3)	(4)
Volatility	-0.0424	0.0026	-0.0174	0.0249
	(0.0415)	(0.0350)	(0.0340)	(0.0333)
Return	-0.0008	-0.0004	0.0037	0.0005
	(0.0012)	(0.0013)	(0.0017)	(0.0014)
Adjusted R-squared	0.1279	0.1112	0.1146	0.1054
Observations	1,126	1,116	1,087	1,022

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 IV
Demand for Insurance Excluding Extreme Days

	(1)	(2)
Volatility	101.1107**	107.9836*
	(37.0563)	(47.9542)
Return	-0.1914	-0.0009
	(0.5029)	(0.5916)
R-squared	0.6614	0.6632
Observations	8,648	8,297

Notes: The dependent variable is the log of the total number of life insurance policies sold on a given day in a given city. Columns (1) and (2) drop dates corresponding to the top 1% and 5% of the distribution of daily volatility. All regressions included controls for city, day-of-week, week-of-year and year. Standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table V
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 city, day of week, week of year, and year. Standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table VI
Loan Performance

Dependent Variable: Indicator equal to 1 if loan defaults

	(1)	(2)	(3)	(4)
Volatility	-6.5526**		-6.9000**	-6.7683**
	(1.8322)		(1.8266)	(2.1379)
Return		-0.1813	-0.1996	-0.1945
		(0.1301)	(0.1262)	(0.1306)
Volatility t-1				-3.5985
				(3.1128)
Volatility t+1				-1.7226
				(1.6031)
Return t-1				0.0152
				(0.1200)
Return t+1				0.0245
				(0.1536)
Adjusted R-squared	0.1651	0.1650	0.1653	0.1653
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, region, 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
Loan Performance Robustness

Dependent Variable: Indicator equal to 1 if loan defaults

	Volatility Measures		Distress Measures		Time Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Volatility	-0.3786**	-0.3772*	-6.8803**	-3.1421	-7.6934**	-4.1870*	-3.1479*
	(0.1032)	(0.1893)	(2.0784)	(1.9493)	(2.3736)	(1.6450)	(1.2515)
Return	-0.2063+	-0.0889	-0.2027	-0.1113	-0.2486+	-0.1561	-0.1346
	(0.1248)	(0.1338)	(0.1248)	(0.1130)	(0.1300)	(0.1368)	(0.1166)
Adjusted R-squared	0.1652	0.1651	0.1675	0.1391	0.1544	0.1606	0.1773
Observations	36,701	36,701	36,701	36,701	34,886	36,292	36,701

Notes: All columns present the results from ordinary least square regressions. Columns (1) and (2) use the daily 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. 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 VIII
Loan Performance Excluding Extreme Days

	(1)	(2)
Volatility	-10.9900**	-17.0877*
	(4.4716)	(4.2601)
Return	-0.1871	-0.2117
	(0.1545)	(0.1999)
R-squared	0.1656	0.1676
Observations	36,292	34,886

Notes: All columns present the results from ordinary least square regressions. Columns (1) and (2) drop dates corresponding to the top 1% and 5% of the distribution of daily volatility. All regressions included controls for region, day-of-week, week-of-year and year. Standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.

Table IX
Firm and Loan Quality

	Credit Rating	*Debt/Asset*	*Loan Size*	*Assets*	*SOE*
	(1)	(2)	(3)	(4)	(5)
Volatility	116.5713*	-28.5109*	79.9545*	29.1076	-7.6013
	(47.4801)	(12.5683)	(35.2101)	(24.6535)	(4.9564)
Return	0.6277	0.5585	1.9151	0.7087	0.1982
	(2.0177)	(0.5127)	(1.2730)	(0.9012)	(0.2231)
Adjusted R-squared	0.1850	0.0450	0.2304	0.2955	0.1300
Observations	17,865	33,674	36,701	35,598	36,701

Notes: All columns present the results from ordinary least square regressions. Credit rating is a numerical rating between 0 and 11, with higher numbers indicating higher credit worthinessLoan size and Assets are the log of the amount in RMB. SOE is a dummy equal to one if the firm is a state owned enterprise. 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 VIII
Number of Approved Loans and Volatility

	All Loans	*Defaulted Loans*	*Performing Loans*
	(1)	(2)	(3)
Volatility	-30.0391**	-182.0788**	-22.0912**
	(8.0903)	(41.3257)	(8.2311)
Return	0.7647*	-1.8264	0.9706**
	(0.3030)	(1.3176)	(0.3114)
Pseudo R-squared	0.5904	0.6116	0.5594
Observations	1,215	1,215	1,215

Notes: All columns present the results from ordinary least square regressions. Columns (1) and (2) drop dates corresponding to the top 1% and 5% of the distribution of daily volatility. All regressions included controls for region, day-of-week, week-of-year and year. Standard errors are clustered on city and date.
+ significant at 10%, * significant at 5%, ** significant at 1%.