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Article (Accepted version)
(Refereed)

Original citation:
Danielsson, Jon and Valenzuela, Marcela and Zer, Ilknur (2018) Learning from history: volatility and financial crises. The Review of Financial Studies, 31 (7). pp. 2774-2805. ISSN 0893-9454

DOI: https://doi.org/10.1093/rfs/hhy049

Learning from History: Volatility and Financial Crises*

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This version: January 2018

Forthcoming: Review of Financial Studies

Abstract

We study the effects of stock market volatility on risk-taking and financial crises by constructing a cross-country database spanning up to 211 years and 60 countries. Prolonged periods of low volatility have strong in-sample and out-of-sample predictive power over the incidence of banking crises and can be used as a reliable crisis indicator, whereas volatility itself does not predict crises. Low volatility leads to excessive credit build-ups and balance sheet leverage in the financial system, indicating that agents take more risk in periods of low risk, supporting the dictum that "stability is destabilizing."

Keywords: Stock market volatility, financial crises predictability, volatility paradox, Minsky hypothesis, financial instability, risk-taking
JEL classification: F30, F44, G01, G10, G18, N10, N20

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1 Introduction

"Volatility in markets is at low levels...to the extent that low levels of volatility may induce risk-taking behavior...is a concern to me and to the Committee." Federal Reserve Chair Janet Yellen.[1]

Do unusual levels of financial market volatility imply an increased likelihood of a subsequent financial crisis? Common wisdom maintains that it does, pointing to the low volatility in the United States in the years prior to the 2008 crisis. It is backed up by the theoretical literature, which finds clear channels for how volatility affects the likelihood of crises. Perhaps the best expression of this view is Minsky's (1977) instability hypothesis, where economic agents observing low financial risk are induced to increase risk-taking, which in turn may lead to a crisis—the foundation of his famous dictum that "stability is destabilizing." Our main objective is to empirically investigate the link between stock market volatility, risk-taking, and financial crises to understand whether prolonged periods of stability lead to systemic events.

The view that economic agents change their risk-taking behavior when financial market risk changes has a long history in the economic literature. Early theoretical work suggests that risk affects economic decisions, especially when it deviates from what economic agents have come to expect. This idea is expressed, for example, in Hayek (1960) and Keynes's (1936) notion of animal spirits. If the resulting risk-taking is excessive, it may, in extremis, culminate in a financial crisis. While there are a number of factors that could cause such an outcome, our interest is in the attitude of economic agents to risk, measured by financial market volatility.

Adverse effects of low volatility on financial stability is consistent with Brunnermeier and Sannikov's (2014) "volatility paradox," where low volatility can paradoxically increase the probability of a systemic event, and Bhattacharya et al. (2015), who examine Minsky's hypothesis in a model with endogenous defaults, where agents update their optimistic expectations during good times, increasing risk-taking. Similarly, Danielsson

[1]Comments from her press conference following the June, 18 2014 FOMC meeting.

et al. (2012) propose a general equilibrium framework with risk constraints, where up on observing low volatility, agents are endogenously incentivized to increase risk.

During low volatility periods, a cause of excessive risk-taking is overoptimism. Agents are not able to measure the actual risk (the underlying latent risk), but they can infer it through the realized market prices, or volatility. Hence, during tranquil periods, when perceived risk is low, economic agents may be misled into taking too much risk. Such a desire to increase risk-taking can manifest itself via two related mechanisms: excess lending and excess leverage. While similar, lending and leverage affect the likelihood of financial crises differently, since we consider lending as aggregate credit across the economy and leverage as the balance sheet composition of financial institutions.

In the model of Simsek (2013), optimistic agents exert a significant impact on collateralized asset prices, ultimately increasing aggregate credit in the economy. In Fostel and Geanakoplos (2014), lenders feel more secure when volatility is low, which encourages them to borrow more. However, such excessive lending may create an adverse outcome, as established in several papers. Greenwood and Hanson (2013) find that in such boom periods, the quality of loans is getting increasingly poor, elevating credit risk. Schularick and Taylor (2012) find strong support for credit booms increasing the likelihood of a banking crisis. More recently, Baron and Xiong (2016) study whether bank equity holders anticipate the severe consequences of credit expansions on financial stability and whether they demand a risk premium as compensation. They demonstrate a presence of overoptimism by bank shareholders during tranquil periods and show that following such overoptimism, bank credit expansion predicts increased bank equity crash risk. Building upon their findings, we study the first element of this feedback loop: Long-lasting periods of low volatility is expected to breed overoptimism, and hence, we test whether low volatility is an important determinant of excessive lending, and in turn increases the likelihood of a banking crisis.

Low volatility can also increase the likelihood of a crisis via financial system balance sheet leverage. Adrian and Shin (2010) find empirically that leverage can be pro-cyclical, increasing during booms. Adrian and Shin (2014) argue that such pro-cyclicality is a consequence of active risk management. Because volatility is an input into risk management processes, low volatility allows financial institutions to take riskier positions for a given threshold and to increase their balance sheet leverage. Thus, in such low volatility periods, financial intermediaries who seek higher yields may lend further or reallocate from safer to riskier assets.

High volatility may also anticipate a financial crisis as it is a signal of growing uncertainty, be it economic, financial, or policy related. Baker et al. (2016) and Gulen and Ion (2016) find that high stock volatility is associated with high policy uncertainty, reducing investment, output, and employment. Engle et al. (2013) show that stock market volatility is related with output and inflation uncertainty. Similarly, in the real options literature, high volatility increases the value of an option to invest, delaying investment (Dixit and Pindyck, 1994) and adversely affecting the economy.

In our empirical investigation of the volatility–crises relationship, we face two paths. We could focus on recent history with ample economic and financial statistics. However, this would limit us to data from the past few decades at best. Since crises are not frequent—once every 37 years for a typical OECD country according to the banking crisis database of Reinhart and Rogoff (2009)—the resulting sample size would inevitably be small. Alternatively, we could exploit long-term historical relationships over multiple decades and centuries, but at the expense of more limited data. We opted for the long-term historical view, believing it to be a better way to obtain statistically meaningful relationships between volatility and crises.

To this end, we construct a cross-country historical database on volatilities, created from monthly returns of real stock market indices. The sample covers 60 countries and spans 211 years, resulting in 3700 country-year observations, with 62 years of historical observations per country, on average. Our main interest is in banking crises, and we use the Reinhart and Rogoff (2009) database.[2] The resulting unbalanced panel contains

[2]To check the robustness of our findings, we also employ alternative banking crisis histories of Bordo et al. (2001); Laeven and Valencia (2008); Gourinchas and Obstfeld (2012); Schularick and Taylor (2012);

a binary indicator of whether a banking crisis starts in a given year and country, and includes 259 distinct banking crises.

The next step is to estimate annual volatilities. While we could have used Engle's (1982) ARCH or Bollerslev's (1986,1987) GARCH models, or some extensions thereof, we opted for realized volatility for two main reasons. First, the evidence of GARCH effects is much weaker in monthly returns than in typical applications with daily returns. Second, GARCH volatilities will revert to a single long-run level, whereas in the long samples as we have, there appear to be more than one long-run volatility level, and realized volatilities are better able to capture this.

To examine whether low volatility predicts crisis, we need to decompose the volatility into high and low components. Borrowing terminology from the output gap literature, we define high and low volatility as the deviations of volatility from above and below its trend, respectively, where trend is estimated through a one-sided Hodrick and Prescott (1997) filter. A one-sided filter uses only past information to estimate the trend for a given time, while a two-sided filter would use future information. This approach is particularly important in our case as we need to quantify what "usual" volatility is. Given that we observe various regimes throughout the history, using the whole sample to estimate long-run volatility would be misleading.

We find that the level of volatility does not predict banking crises, while prolonged periods of low volatility do. Low volatility has a strong in-sample and out-of-sample predictive power over the incidence of a crisis. The economic impact is the highest if the economy stays in the low volatility environment for five years: a 1% decrease in volatility below its trend translates to a 1.01% increase in the probability of a crisis. We further show that low volatility delivers a strong signal-to-noise ratio, significantly beating random noise, suggesting that it can be used as a reliable crisis indicator by policymakers. The results are robust to different definitions of volatility and alternative

Romer and Romer (2015). The results are qualitatively similar to using Reinhart and Rogoff (2009), so we opted for the latter as it is the most comprehensive one both in time-series and cross-sectional dimensions.

model specifications. Finally, we find weak evidence that high volatility increases the likelihood of banking crises.

We then investigate the two mechanisms for how low volatility may lead to a financial crisis: excess credit and leverage. We are unable to test them with our entire historical dataset as credit and balance sheet leverage data are limited in both the time and the cross-section dimensions. By using BIS data from the 1960s for 37 countries, we find that long-lasting periods of low volatility induce excessive lending. We then use the cross country balance sheet leverage (assets/equity) data of Lee et al. (2017), which cover 31 countries spanning from 1980s and find that the financial sector leverage increases following low volatility periods, even after controlling for lending growth. These results suggest that financial system stability endogenously creates instability through lending booms and excess leverage.

Finally, splitting our 211-year sample into various sub-periods, we find that the relationship between financial market volatility and the incidence of a crisis becomes stronger over time—not surprising, considering that prior to World War I, stock markets, and hence market volatility, played a much smaller role in the economy than they would later.

Financial market volatility is of clear interest to policymakers, as seen by the opening quote from Chair Yellen. Within the post-2008 crisis macroprudential agenda, policymakers are actively searching for signals of future financial and economic instability and developing policy tools to mitigate the most unfortunate outcomes. Volatility is a key ingredient in some indicators, such as the European Central Bank's Systemic Stress Composite Indicator. Our results indicate that it might be better for policy authorities to include low volatility as a crisis indicator since an observation of current low volatility implies that a future crisis is more likely.

2 Data and descriptive analysis

2.1 Volatility

We construct a database on historical volatility for 60 countries, some dating back to 1800 by using stock market price data from Global Financial Data (GFD), a database that specializes in aggregating data collected by economic historians. We use monthly stock prices as daily prices are quite scarce. While we can go back to the early 20th century for the United States, for the rest of the countries daily price data only exists from the second part of the 20th century. Moreover, since we are interested in the effects of volatility on financial crises, where the latter is measured at the annual frequency, monthly stock market returns are sufficient.

Table 1 shows the list of the 25 developed and 35 emerging countries in our sample (based on the IMF's classification), sample coverage, and the names of the market indexes. Only data for the United States and the Great Britain are available from 1800, while we have data for France, Germany, and Australia from the mid-19th century. A large number of countries developed stock markets after the World War I. All the sample countries have data for 2010, except Zambia.

Since many of the countries in the sample have experienced high inflation at times, it is necessary to adjust the stock market data for inflation, for which we use the consumer price index (CPI) data from GFD.[3] Not surprisingly, in such a comprehensive sample, a number of extreme observations occur, often due to disruptive events like war and hyperinflation. In such cases, volatility estimates are likely to be biased and consequently it may be preferable to bound extreme observations (Han, 2013). Hence, in baseline specifications, we winsorize 1% of monthly real returns. More specifically, if a given country's real monthly return is above its 99.5th percentile, we set the return at the top

[3] For 30% of the observations monthly CPI is not available and we use linear interpolation to obtain monthly CPI. This interpolation should not be problematic because the CPI moves much more slowly than the stock markets and therefore any interpolation error would only marginally affect the volatility. Indeed, the average correlation of volatilities across countries, calculated using nominal or real returns, exceed 0.98 and our main findings are unaltered when we estimate volatility using nominal returns.

99.5th percentile value. Note that the main results hold regardless of whether we use non-winsorized returns or winsorization at the 1% and 5% level.

The next step is to model volatility, both to capture shorter-term volatility clustering and longer-term level changes. The volatility literature emphasizes two main approaches. The first is the direct modeling of autoregressive volatility, as pioneered by Engle's (1982) ARCH process. For example, we could have used Bollerslev's (1986,1987) GARCH model, or other extensions.[4] The main alternative to the (G)ARCH class of models is realized volatility; the standard deviation of returns over a sample period. The choice of which modeling approach is the best to take depends to a considerable extent on the sampling frequency. The available literature, for example French et al. (1987), finds that neither GARCH nor realized volatilities are inherently better in their application of daily returns and monthly volatilities. In our case, realized volatility is a better choice. Not only is the evidence of GARCH effects much lower in monthly returns than in typical applications with daily returns (e.g., Zivot, 2009), GARCH volatilities will revert to a single long-run level, whereas in the long sample we have, there appear to be more than one long-run volatility levels and for situations where volatility changes rapidly to a new level, GARCH volatilities would be slow at "catching up" (Andersen et al., 2003). We did evaluate a GARCH(1,1) model and the absolute value of returns as alternative volatility estimators in the robustness analysis and find that our results do not change qualitatively.

We estimate the annual volatility as the standard deviation of 12 monthly returns using mid-year observations. Specifically, monthly returns from July in year $t-1$ up to June in year t are used to calculate volatility in year t, so the volatility estimates use non-overlapping samples of returns. While it might seem natural to use January to December as the 12 month-period, in our database we do not know the starting month of a crisis. Even if it were marked, it is hard to verify the precise timing of a crisis as

[4]There is an extensive literature on volatility modeling following from the ARCH/GARCH models, including the ones that develop methods to identify long-run and short-run volatility, like Engle and Rangel (2008); Adrian and Rosenberg (2008), FIGARCH (Baillie et al., 1996), and the MIDAS class of models (see e.g. Chen and Ghysels, 2011).

it could have realistically started earlier. For instance, an actual bank run or receipt of government assistance usually comes well after the financial problems start. In such a case, volatility estimates from January to December would overlap with periods of financial distress, especially for a crisis that hits early in the year. Hence, to minimize the impact of crisis on volatility, we opted to leave 6 months of gap and use mid year returns. In Section 5, we show that the results are not sensitive to the chosen period to calculate annual volatility.

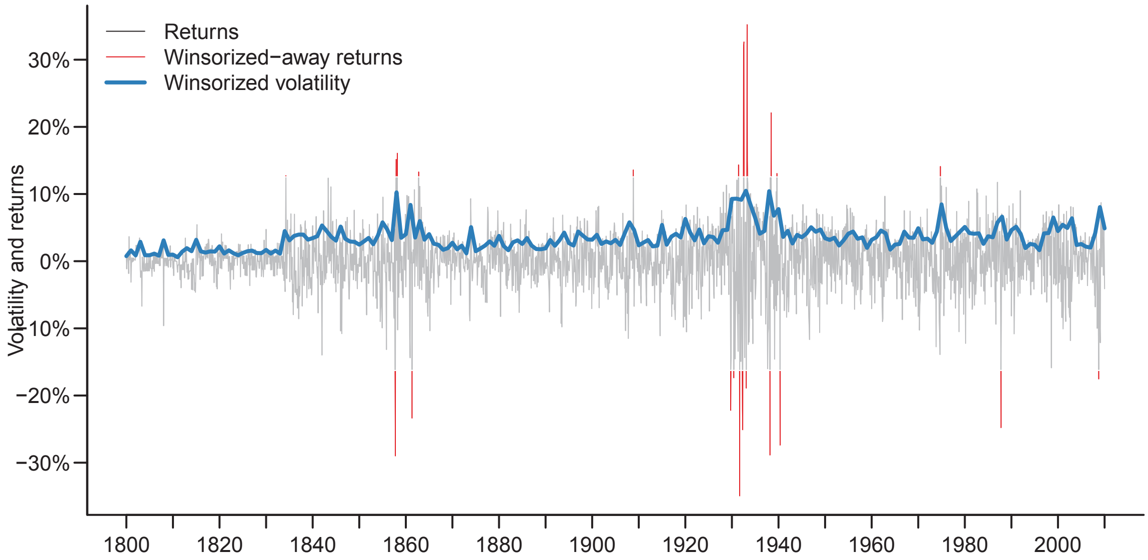
Figure 1 shows the time-series plot of annual volatility for the United States, the monthly real returns and the resulting winsorized annual volatility, while the Web Appendix, `www.ModelsandRisk.org/volatility-and-crises`, contains similar analyses for every country in the sample. In line with earlier studies, such as Officer (1973) and Schwert (1989, 1990), we see that many periods of high volatility in the United States correspond to recessions and crises. The highest volatilities are observed during the Great Depression and the late 1930s recession, followed by the 1850s recession, the early 1970s recession, the 1987 crash, and the 2008 Global Financial crisis. In the entire sample, all episodes, where winsorization is applied correspond to wars, major crises, and/or hyperinflation periods.

2.2 Descriptive analysis: volatility

Within our 211 years of historical sample period, we witness many different economic and market structures that dramatically affect the stock market developments and financial volatility. In the beginning of the sample, we have very few countries and no electronic communication, while by 2010 we have advanced integrated financial and economic systems. Stock markets have become steadily important over time. In the earliest part of the sample, few economic agents had access to stock markets and banking. While individual bank accounts had become quite common in the United Kingdom by the mid-1800s, that was not the case for the other early history countries (Elliot, 2006).

Figure 1: Return and volatility estimates, United States

In this figure, we present monthly real stock market returns, winsorized at the 1% level, and the winsorized annual volatility estimates for the United States. Volatility is calculated as the standard deviation of 12 monthly real returns.



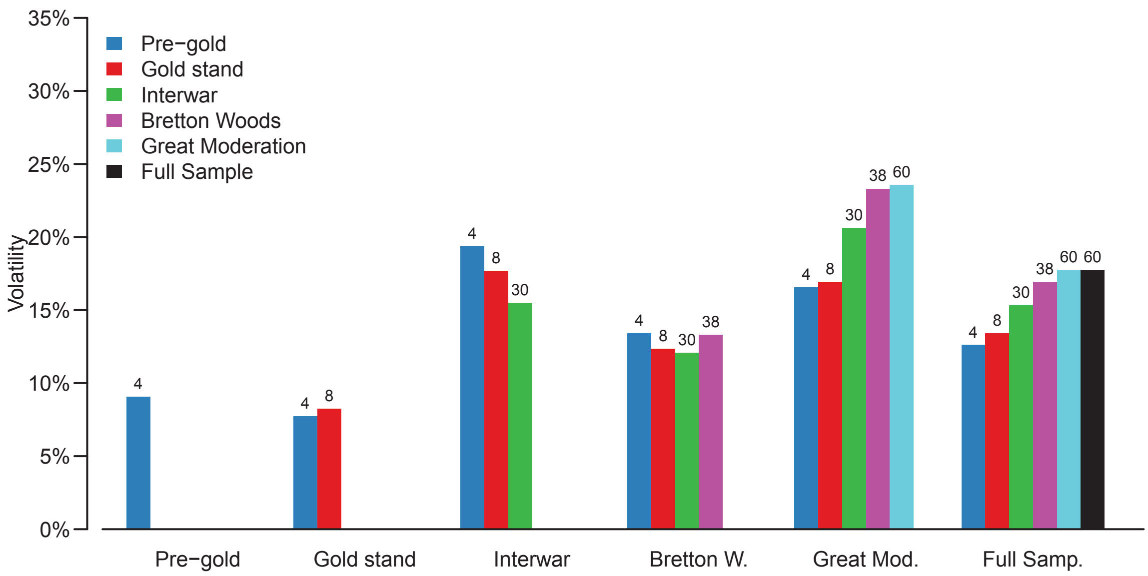
Stock markets first start to play a major economic role in the interwar years, and then primarily in the United States.

Figure 2 shows the average volatility and monthly return correlations, focusing on different periods. Although there are many interesting periods within our sample that merit special attention, to keep the discussion tractable, we focus on six: the pre-gold period (1800–1872), the gold standard era (1873–1913), the interwar years (1919–1938), Bretton Woods (1949–1972), the Great Moderation (1985–2006), and finally the whole sample.

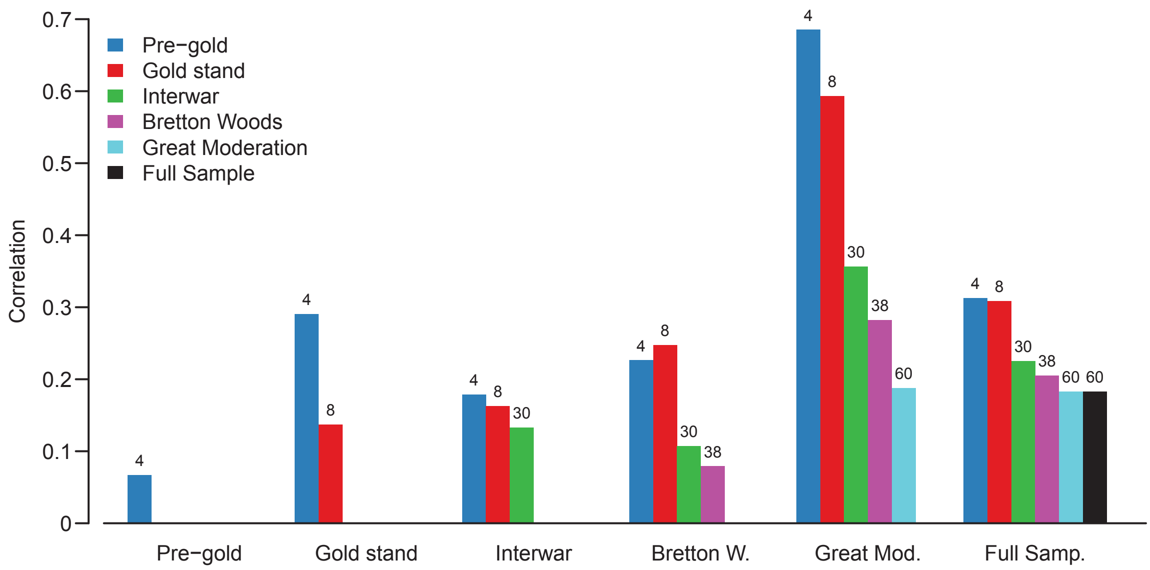
For each time period, we first calculate the volatility of a given country or bilateral correlations, and then, we report the cross-sectional averages. To ensure comparable results, we keep the same set of countries across time. When new countries enter the sample, we identify them with a new colored bar. For instance, a blue bar in all of the panels corresponds to the four countries used to calculate the metric whose data is available in the pre-gold period, namely USA, UK, France, and Germany. The total

Figure 2: Volatility and correlations: sub-periods

In Panels (a) and (b), we present the average volatility and monthly return correlations for different periods ,respectively. Given the time period, we first calculate the volatility for each country, and then, we calculate the cross-sectional averages. Each color corresponds to a group of countries that kept across time. For instance, the blue bar in Panel (a) corresponds to the group of countries used to calculate the metric whose data is available in the pre-gold period. After calculating bilateral correlations, we report the cross-sectional averages. The pre-gold (1800–1872), gold (1873–1913), interwar (1919–1938), Bretton Woods (1949–1972), and the Great Moderation (1985–2006) periods as well as the whole sample period (1800–2010), are considered. Volatility is calculated as the standard deviation of the previous 12 winsorized monthly real returns, scaled by $\sqrt{12}$, and the whole sample includes 60 countries. The total number of countries for which we have data and used to calculate averages/correlations in a given time period is reported on top of each bar. Emerging and developed countries' classifications are adopted from the IMF definition.



(a) Average volatility



(b) Average correlations

number of countries for which we have data and used to calculate averages/correlations in a given time period is reported on top of each bar.

For most of the pre-gold period, only two countries are present in the sample, the United States and the United Kingdom and they are only linked by electronic communication from 1858. Germany and France emerge around the middle of the 19th century. Hence, not surprisingly, the correlation between the sample countries is low at about 7% and volatilities are below the sample average. During the gold standard, in a period of rapid economic growth and globalization, we observe the lowest volatilities in the sample and increased correlations. During both periods, financial markets are essentially unregulated, and the number of limited liability corporations is relatively small, but growing over time. Almost all banks are partnerships and hence have different incentives of risk-taking to their modern counterparts, which are mostly limited liability corporations.

Equity markets start to become increasingly important vehicles for investment and financing during the interwar era. After World War I, more countries, including emerging ones, develop stock markets and hence entering into our sample. We observe that volatilities increase considerably during this era. During the Bretton Woods era, financial markets become highly regulated and international capital flows are severely restricted, limiting cross-border investment. Not surprisingly, volatilities fall notably. When the Bretton Woods system collapses, markets become more deregulated, electronic trading emerges and international capital flow restrictions are lifted, both correlations and volatilities increase sharply, reaching their maximum during the Great Moderation (1985–2006) period. Markets in developed countries are especially correlated due to the effects of globalization and widespread use of electronic trading.

2.3 Decomposing volatility into high and low

Figure 1 suggests that the long-run level of volatility for the United States is not constant, exhibiting a slow-moving, non-monotone trend spanning multiple decades. Similar patterns exist for other countries. Furthermore, volatility differs considerably across countries. These two combined effects—the presence of a slow-moving trend and heterogeneous volatility levels—need to be addressed in the empirical analysis since a particular measurement of volatility could be seen as high, low, or typical, depending on the country or year.

We do that by decomposing volatility with the Hodrick and Prescott (1997) (HP) filter into trend and deviation from trend, in different contexts referred to as cycle.[5] The HP filter is based on using a smoothing parameter λ, which quantifies the degree to which volatility deviates from its trend. The volatility trend is obtained from the following optimization problem:

$$\min_{\{\tau_t(\lambda)\}_{t=1}^{T}} \sum_{t=1}^{T} [\sigma_t - \tau_t(\lambda)]^2 + \lambda \sum_{t=2}^{T-1} \{[\tau_{t+1}(\lambda) - \tau_t(\lambda)] - [\tau_t(\lambda) - \tau_{t-1}(\lambda)]\}^2 , \tag{1}$$

where σ_t is volatility and $\tau_t(\lambda)$ is trend, which is a function of λ. The higher the λ, the smoother the trend. The choice of λ depends on the nature of the underlying series being filtered. With annual GDP, λ is typically set at 6.25. For a clustering time-series like volatility, a larger λ is needed, otherwise, the procedure would assign a very large fraction of temporary swings to the trend making it almost the same as volatility itself. However, a very large λ is not ideal neither as increasing the persistence of the filter may remove long-run factors such as structural changes in the financial or regulatory system. Hence, we set $\lambda = 5000$, but as discussed in the robustness section, our results are invariant to a range of values.

As our analysis builds on predictive regressions, we use only past information when constructing the explanatory variables. This implies using a one-sided HP filter, con-

[5]Alternatively, one could adopt Markov switching models, for modeling the trend levels of volatility, along the lines of Hamilton and Susmel (1994). However, given our sample size, with Markov switching we are limited to most two regimes, and in addition the distinction between the regimes is sharp, we jump from one to the other. Our data indicates that there are more than two regimes and the transition from one to the other is relatively smooth.

structed by running the HP filter recursively through time by using only data available up to year t to estimate the trend for year t.

In order to identify the high and low volatility channels, we further separate the deviation of volatility from its trend into two components, high and low volatility, denoted by $\delta_{\mathrm{t}}^{\mathrm{high}}(\lambda)$ and $\delta_{\mathrm{t}}^{\mathrm{low}}(\lambda)$, respectively.

$$\begin{aligned}
\delta_{\mathrm{t}}^{\mathrm{high}}(\lambda) &= \begin{cases} \sigma_t - \tau_t(\lambda) & \text{if} \qquad \sigma_t \geq \tau_t(\lambda) \\ 0 & \text{otherwise,} \end{cases} \\
\delta_{\mathrm{t}}^{\mathrm{low}}(\lambda) &= \begin{cases} \sigma_t - \tau_t(\lambda) & \text{if} \qquad \sigma_t < \tau_t(\lambda) \\ 0 & \text{otherwise.} \end{cases}
\end{aligned} \tag{2}$$

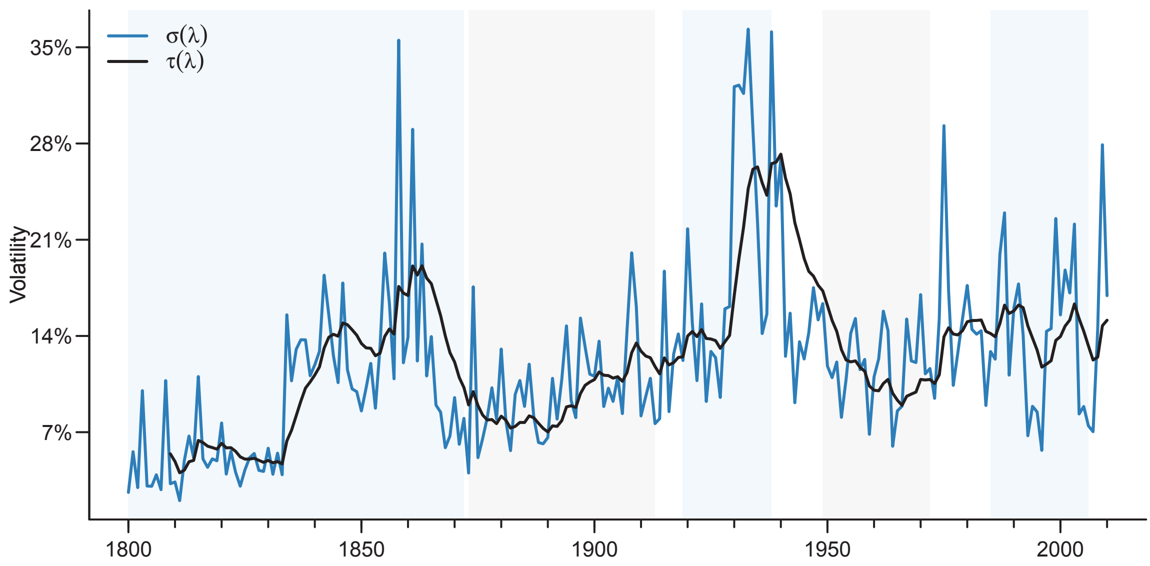
Figure 3 visualizes the volatility, trend, and high and low components of volatility for the United States, with the corresponding plots for the rest of the countries remanded to the Web Appendix. Note that due to data limitations, we could not estimate the trend for Bolivia and Zambia. In Table 2, we present the cross-sectional and time-series mean, median, and standard deviation of annual volatility, and high and low components, for the whole sample, emerging, and developed countries separately. Annual volatility is higher for the emerging countries, with Turkey reaching over 50% on average. Volatility deviates from its long-run level by about 3% up and down on average, and the deviation is higher for emerging countries compared to the developed ones.

2.4 Financial crisis data

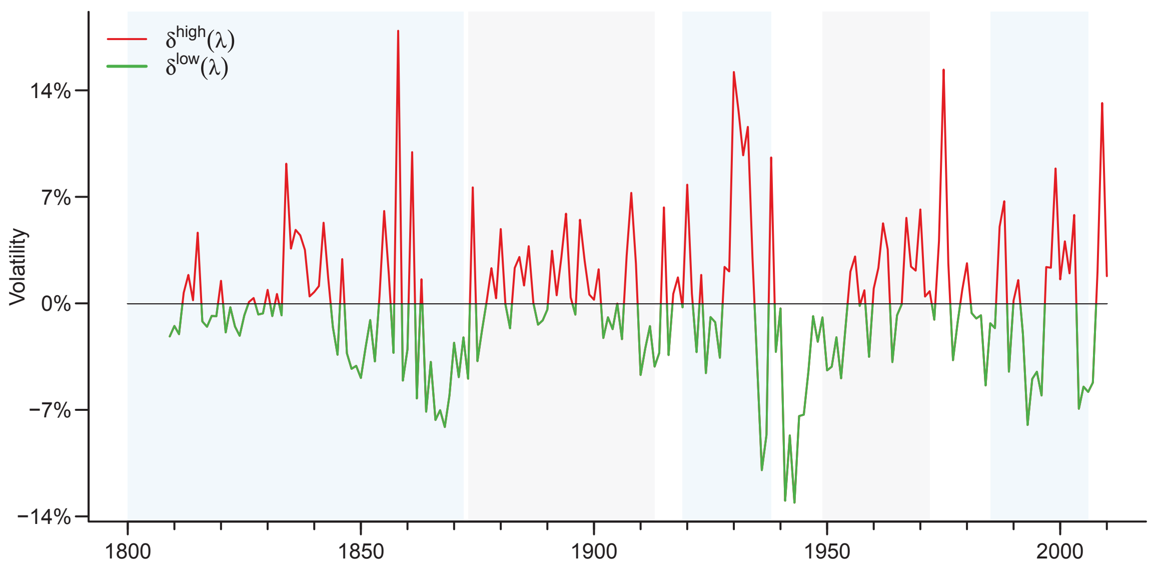
We base our analysis on the banking crises in Reinhart and Rogoff's (2009) database. A banking crisis is defined as an event with a closure, merger, or public takeover of one or more financial institutions or large scale government assistance of a systemically important financial institution. The sample includes 60 countries with both volatility and banking crisis data coverage. In total, we observe 259 banking crises, which combined with volatility data lead to a sample of 3700 country-year pairs.

Figure 3: Estimated trend and high and low volatility, United States

Annual volatility level (σ) and estimated trend (τ) for the United States. Volatility is calculated as the standard deviation of the previous 12 winsorized monthly real returns scaled by $\sqrt{12}$. Then, the Hodrick and Prescott (1997) filter with a smoothing parameter of $\lambda = 5000$ is applied to decompose volatility level into trend and deviations from the trend. In Panel (b), we plot high and low volatility—δ^{high} and δ^{low}—introduced in (2). The pre-gold (1800–1872), gold (1873–1913), interwar (1919–1938), Bretton Woods (1949–1972), and the Great Moderation (1985–2006) periods are highlighted.



(a) Trend and volatility

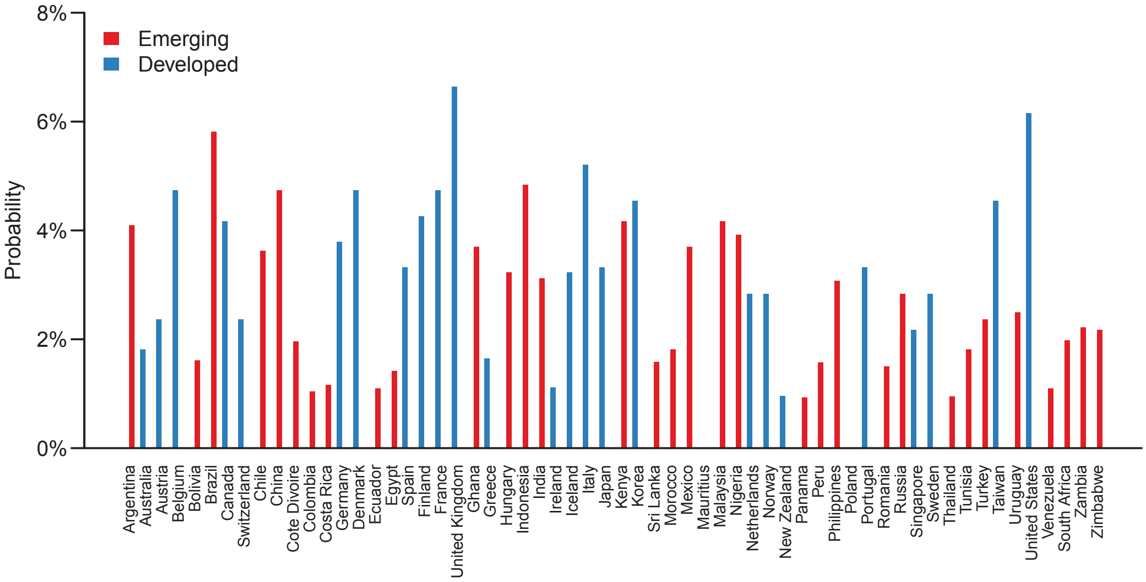


(b) High and low volatility

The unconditional probability of banking crises, defined as the number of crisis divided by the available sample period, is higher on average for the developed countries (Table 2 Column IV), suggesting an association between development and the intensity of a banking crisis.[6] Figure 4 shows that within the developed countries, the United Kingdom has the highest annual crisis probability at 6.64%, and New Zealand the lowest at 0.96%. For emerging countries, the annual unconditional crisis probability ranges from 0% in Mauritius and Poland to 5.82% for Brazil.

Figure 4: Unconditional annual probability of banking crises

The figure presents the probability of banking crises for emerging and developed countries. For a given country, the probability of a banking crisis is calculated as the number of crisis divided by the available sample period.



2.5 Control variables

While testing the effects of unusual volatility on crises, we include a number of variables known to be predictors of crises as controls, using several sources. We use the natural logarithm of GDP per capita ($\ln GDP$), introduced in Maddison (2003). The database

[6] In an early study, Bordo et al. (2001) find that banking crises are more common for emerging countries. The identification of crises does not vary considerably between the Reinhart and Rogoff (2009) and Bordo et al. (2001) databases. The difference is mainly driven by the different countries and time periods covered by the two datasets and the different classification of the countries as emerging and developed.

provides a widely used resource for historical GDP data with regular updates available on `http://www.ggdc.net/maddison/`, and has been used in a number of studies, including Acemoglu et al. (2008) and Reinhart and Rogoff (2009).

Inflation affects the likelihood of a financial crisis (see e.g., Demirguc-Kunt and Detragiache, 1998). We calculate inflation as the annual percentage change in the consumer price index, obtained from GFD. As government debt may affect the probability of a crisis, we also include $\Delta PD/GDP$, the change in gross central government debt-to-GDP ratio. The data is obtained from Reinhart and Rogoff (2011).

Institutional characteristics and governance of a country can affect political and macroeconomic stability (see e.g., Cerra and Saxena, 2008). We therefore use the POLCOMP variable from the Polity IV Project database as a proxy for "institutional quality".[7] POLCOMP is the combination of the degree of institutionalization or regulation of political competition, and the extent of government restriction on political competition. The higher the value of the POLCOMP, the better the institution quality of a given country.

Table 2, Columns V through VIII presents summary statistics for the control variables. Emerging countries have lower GDP per capita and institutional quality and higher levels of inflation than developed countries, on average. The differences are statistically significant at the 5% level. We observe a considerable time-series and cross-country variation in change in the debt/GDP ratio and inflation, but much less variation for GDP and political competition.

[7]As an alternative, we repeat the analysis using the Political Constraint Index Dataset (POLCON) of Henisz (2002). POLCON and POLCOMP are over 65% correlated and and our results are similar regardless of the series employed.

3 Effects of volatility on financial crises

3.1 Econometric methodology

We regress the binary crisis indicator $C_{i,t}$, which shows whether a banking crisis started in country i in year t, on different specifications of volatility and control variables, $X_{i,t}$, all introduced in Section 2. We first analyze the impact of volatility on banking crises by including the level of volatility as the main regressor. We then investigate whether the impact of volatility on banking crises is asymmetric by considering the absolute value of the deviation of volatility from its trend, as a regressor. Finally, we examine the effect of high and low volatilities separately by including $\delta_{i,t}^{\text{high}}$ and $\delta_{i,t}^{\text{low}}$ as regressors.

Instead of regressing the crisis indicator on lags of the explanatory variables, we follow Reinhart and Rogoff (2011) and use backward-looking moving averages of explanatory variables over L lags, from $t-1$ to $t-L$. This procedure, in addition to reducing the collinearity between the explanatory variables, allows us to measure high and low volatility for a prolonged period of time, smoothing out temporary volatility spikes. For country i and year t, we estimate the following logit-panel regression:

$$\begin{aligned} \text{logit}(C_{i,t}) = \quad & \alpha\overline{C}_{i,t-1 \text{ to } t-L} + \beta\overline{\Gamma}_{i,t-1 \text{ to } t-L}(\lambda) + \gamma\overline{X}_{i,t-1 \text{ to } t-L} \\ & +\nu_t + \eta_i + \varepsilon_{i,t}, \quad i = 1, \cdots, N \end{aligned} \tag{3}$$

where $\text{logit}(C) = \log(C/(1-C))$ is the log of the odds ratio, Γ is one of σ, $|\sigma-\tau|$ or $[\delta^{\text{high}}\ \delta^{\text{low}}]'$, λ is the HP filter smoothing parameter, ν_t and η_i are the time-series and cross-sectional fixed effects, respectively. The moving average variables are constructed as:

$$\overline{z}_{i,t-1 \text{ to } t-L} = \frac{1}{L}\sum_{j=1}^{L} z_{i,t-j}, \quad z = C, \sigma, |\sigma-\tau|, \delta, X. \tag{4}$$

When we use year and country fixed effects we face identification issues since crises are rare events. Thus, we opted to use less granular fixed effects at the decade and region level of aggregation.[8] Throughout the analysis, we dually cluster standard errors both on country and year levels to address possible time-series and cross-country correlation of residuals.

3.2 Empirical results

Table 3 presents the results for the panel-logit regressions introduced in (3), where we consider the last five years' information ($L = 5$). The first relationship we consider is how volatility relates to the probability of future crises, perhaps the higher the volatility, the more likely a crisis occurs. The results are presented in Columns I and II. When considered on its own as an independent variable, volatility is statistically significant, but the significance does not survive the inclusion of control variables. This result suggests that any impact of the level of volatility on the likelihood of future crises is fully captured by the control variables, especially the debt-to-GDP ratio and inflation.

By contrast, the absolute value of the deviation of volatility from its trend, $|\sigma_{i,t} - \tau_{i,t}|$, is significant as can be seen in Columns III and IV. In other words, when volatility moves away from the trend, in either direction, the more likely a crisis is.[9]

To investigate further, we include high and low volatilities defined in (2) as separate regressors, reported in Columns V and VI. The coefficients of both δ^{high} and δ^{low} are significant with expected signs in the absence of control variables: $\beta_{\delta^{\text{high}}} > 0$ and $\beta_{\delta^{\text{low}}} < 0$. However, only δ^{low} survives the inclusion of control variables: low volatility affects

[8]We construct dummies for each decade as follows: The first decade starts in 1800 and ends in 1809. The second decade is from 1810 to 1819, etc. We recognize that the chosen fixed effects may potentially play a role in generating the results. To check the stability and robustness of our results, we first repeat the analysis without any fixed effects and with 5 year fixed effects. We also construct decade fixed effects starting in years ending in 1 (i.e., 1801-1810, 1811-1820 etc), ending in 2 (i.e., 1802-1811, 1812-1821 etc) up to years ending in 9 (1809-1818, 1819-1828 etc). In all of the cases we find similar results (see the Web Appendix Table A.1).

[9]To investigate whether volatility has a breaking point at its trend, we consider a specification with the deviation of volatility and the squared of the deviation, $\sigma - \tau$ and $(\sigma - \tau)^2$, as explanatory variables. We find the coefficient of the deviation term is negative and insignificant whereas the coefficient of the quadratic term is positive and significant. Moreover, the estimated turning point equals to 1.46 with a confidence interval of [-2.47, 5.37], hence, statistically not different from 0. We also explore higher power specifications, rejecting a cubic specification in favor of a quadratic one.

agents' decision making, induces excessive risk-taking, leading to future credit problems and difficulties for banks. The estimated marginal effects (ME) show that the impact of low volatility on the probability of crisis is economically meaningful: A 1% decrease in volatility, when it is below its trend, translates into a 1.01% increase in the probability of a banking crisis.

Taken together we find that the effect of volatility on crises depends on whether the system is in an unusually high or low volatility state. Indeed, a hypothesis $H_0^a : \mathrm{ME}_{\delta^{\mathrm{high}}} = \mathrm{ME}_{\delta^{\mathrm{low}}}$ is rejected at the 1% level, suggesting that increasing volatility in a high state has a different effect than increasing volatility in a low state. Hence, we reject the common assumption of a positive relationship between volatility and the likelihood of crises and provide a new evidence that prolonged periods of low volatility increase the probability of crises. That leaves the question of whether the impact of high volatility is the same as that of low volatility. Although the coefficient of high volatility is insignificant, the marginal effects of high and low volatility are not statistically distinguishable from each other, as the hypothesis $H_0^b : |\mathrm{ME}_{\delta^{\mathrm{high}}}| = |\mathrm{ME}_{\delta^{\mathrm{low}}}|$ cannot be rejected at a 5% level, most likely due to the high standard error of high volatility.

Our findings presented so far rely on backward moving averages of explanatory variables using the previous five years ($L = 5$). In Table 4, we examine the predictive power of low volatility by using different lag lengths. The results show a negative and economically significant relationship between low volatility and future financial crises when information up to 10 years is taken into account to calculate the historical average of low volatility. Marginal effects reported at the end of the table show the change in the probability of banking crises following an instantaneous change in high or low volatility. We find that a 1% decrease in volatility below its trend translates into a 0.64%, 0.68%, 1.01%, and 0.84% increase in the probability of a banking crisis if the last 1, 2, 5, and 10 years' information is used, respectively. The marginal effects increase monotonically and reach a maximum when last five years are considered, indicating that the economic impact is the highest if the economy stays in the low volatility environment for five years. This finding is intuitive: to alter agents' expectations and allows for imbalances to build-up, volatility should be persistently low, for at least few years. After long periods though, unusually low volatility becomes "usual" and agents are not likely to continue taking excessive risk during such conditions.

In addition to the volatility components, we find that the lagged crises is significant with a negative sign, suggesting that countries that have had crises during the last 5 years are less likely to face another one in the future. This may happen, for example, if agents become more risk averse in the immediate aftermath of a crisis than they otherwise would be.

Morever, higher institutional quality of a country (POLCOMP) significantly lowers the probability of a banking crisis. It could be that governance is better for countries with better quality scores, where it is more difficult for politicians to distort banks' lending decisions. An increase in the debt-to-GDP ratio is negatively associated with the probability of a future banking crisis. This is consistent with the experience of the European sovereign debt crisis. Iceland and Ireland, the two countries where the banking system was the most direct cause of the sovereign crisis, had low initial sovereign debt levels, whereas the more indebted crisis countries, such as Portugal and Greece, had more conservative banking systems that only suffered as a consequence of the sovereign difficulties.

3.3 Reliability of low volatility as a financial crisis predictor

While our results show that current deviations of volatility from its long-run trend indicate that a financial crisis is more likely a few years down the road, they do not by themselves suggest that low volatility is a valuable crisis indicator, which would be of interest for policymakers. We examine such predictability along two dimensions. First, we formally evaluate the degree of the signal-to-noise ratio, i.e., the tradeoff between the signaled true positives (the fraction of correctly predicted crises) to false positives (the fraction of false alarms). Second, we examine the out-of-sample forecasting performance of low volatility, as in-sample regressions may be affected by look-ahead bias even though we use lagged variables and one-sided filtering methods.

For low volatility to be used as an early warning indicator (EWI), it needs to provide accurate signals on crisis probabilities. This signaling approach is widely used to statistically evaluate the usefulness of an indicator following the work of Kaminsky and Reinhart (1999). Recently, built on this approach, a more general evaluation criteria—the area under the receiving operating curve (AUROC)—has gained considerable attention (See for example, Bharath and Dittmar, 2010; Berge and Jorda, 2011; Schularick and Taylor, 2012).[10]

To obtain the AUROC in our setting, we first run the baseline regression (3) while removing all of the explanatory variables but low volatility, and obtain predicted crisis probabilities. We then compare the predicted probability with various probability thresholds and compute the corresponding true and false positive rates, reaching an AUROC value of 76%, with a 95% confidence interval of $[72\%, 80\%]$.

There is no established benchmark in the literature for AUROC results. A value of 50% indicates that a model is no better than a signal provided by a coin toss, while 100% means perfect predictability. Then, how "high" is an AUROC of 76%? For comparison, Bharath and Dittmar's (2010) model on which firms go private delivers an AUROC of 78%, and Berge and Jorda (2011) study the predictive ability of various indicators on economic turning points and report AUROC values ranging from 0.66 to 0.98. In the study most related to ours, Schularick and Taylor (2012) find an AUROC of 72% for the predictive ability of credit expansion on banking crises. To make the results more comparable, we keep the same sample of Schularick and Taylor's (2012) with their definition of banking crises and run our baseline specification. With the caveat that the

[10] A major drawback of the signal-to-noise ratio is that it relies on a specific threshold, which reflects the policy makers' preferences and loss function. For example, the lower the threshold, the more signals will be observed, suggesting that policy-makers put a lot of weight on catching a crisis, even if it is falsely alarmed. The signal is extracted from the estimated indicator when it breaches such pre-determined threshold. On the other hand, as AUROC plots the true positive against the false positive rates for various threshold values, it does not require an assumption on the threshold value and hence, on the policy makers' preferences.

models used in the two papers are different, we find that low volatility alone delivers an AUROC of 80%, whereas credit growth and low volatility together increase the AUROC up to 85%.

To evaluate the out-of-sample performance, we first run (3) by including only low volatility as a regressor. Using data up to 1980, we estimate the predicted probability of a crisis for each country for 1981. Second, we repeat this analysis rolling forward each year from 1980 up to 2010, such that the pre-1982 period is used to predict crises in 1982, and then pre-1983 period is used for crises in 1983, so on and so forth. Finally, we calculate the cross-sectional averages of pseudo-R^2 of Estrella and Mishkin (1998). If low volatility provides an accurate forecast, then we should observe a positive pseudo-R^2. We calculate the pseudo-R^2 for a range of estimation periods, finding positive values in all cases. For example, setting the training period to 1980 and 1960, the pseudo-R^2 is 22.2% and 18.0%, respectively.

Our results suggest that relatively low volatility provides a statistically significant indication of future crises both in-sample and out-of-sample, delivering a strong signal-to-noise ratio. Hence, it should be seriously considered by policymakers as an early warning indicator of crises.

4 Why does low volatility lead to financial crises?

The results above can be supported by a low risk environment breeding over-optimism and hence encouraging economic agents to engage in excessive risk-taking that ultimately triggers a crisis—what is often termed the "Minsky hypothesis" (see, for instance, Bhattacharya et al., 2015). We further explore two possible mechanisms of why low volatility may lead to a financial crisis.

The first mechanism is excessive lending. In the model of Simsek (2013), optimism related to the relative probability of upside states increases asset valuations and the ability of agents to increase credit in the economy. Fostel and Geanakoplos (2014) argue that low volatility makes lenders feel more secure and lend more. However during a credit boom, the quality of loans gets increasingly poor as lenders associate such periods with low probability of default (Greenwood and Hanson, 2013). Eventually, the number of defaults grows, putting banks under ever higher strain and ultimately increasing the likelihood of a banking crisis. In other words, the stability in the financial system endogenously creates financial instability. The link of credit booms leading to distress has been studied by Schularick and Taylor (2012) and Baron and Xiong (2016), who find that excessive lending adversely affects the likelihood of banking crises and bank equity crash risk, respectively. As low volatility is expected to breed overoptimism, that leaves the question of whether volatility affects excess credit.

The second mechanism is excessive financial institution leverage. Adrian and Shin (2010) find empirically that financial institution leverage can be pro-cyclical, increasing during booms. Adrian and Shin (2014), argue that such pro-cyclicality is a consequence of active risk management: because volatility is an input into risk management processes, a perception of low volatility allows financial institutions to take riskier positions for a risk exposure threshold and increase leverage.

Limiting ourselves to the most recent history, we are able to test the excess credit mechanism by using aggregate private non-financial sector credit data, as a percentage of GDP, from the BIS. The data cover 37 countries from the 1960s. To study balance sheet leverage, we use the financial sector assets over equity data of Lee et al. (2017), which covers 31 developed and emerging countries from 1980s. The data are hand-collected from several sources, including central banks, regulatory authorities, and the BIS, and aggregates data from commercial banks, broker dealers, and other financial institutions.

To examine whether low volatility for a prolonged period of time leads to excess credit or leverage, we run the following panel regression:

$$\begin{aligned} Y_{i,t}(\lambda) = \;& \beta_1 \overline{\delta}^{\text{high}}_{i,t-1 \text{ to } t-L}(\lambda) + \beta_2 \overline{\delta}^{\text{low}}_{i,t-1 \text{ to } t-L}(\lambda) + \beta_3 \overline{Y}_{i,t-1 \text{ to } t-L}(\lambda) \\ & + \beta_4 \overline{X}_{i,t-1 \text{ to } t-L} + \beta_5 \overline{IR}_{i,t-1 \text{ to } t-L} + \nu_t + \eta_i + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

Here, X denotes the control variables introduced in (3) and the level of interest rates (IR) is included as it is expected to be an important determinant of credit growth. The dependent variable $Y_{i,t}$ is either high credit ($\delta^{\text{high}}_{\text{CR}\ i,t}$) or high leverage ($\delta^{\text{high}}_{\text{LR}\ i,t}$) calculated analogous to high volatility:

$$\delta^{\text{high}}_{\text{CR}\ i,t}(\lambda) = \begin{cases} \text{CR}_{i,t} - \tau_{\text{CR},i,t}(\lambda) & \text{if} \qquad \text{CR}_{i,t} \geq \tau_{\text{CR}i,t}(\lambda) \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

$$\delta^{\text{high}}_{\text{LR}\ i,t}(\lambda) = \begin{cases} \text{LR}_{i,t} - \tau_{\text{LR},i,t}(\lambda) & \text{if} \qquad \text{LR}_{i,t} \geq \tau_{\text{LR}i,t}(\lambda) \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

where CR is credit-to-GDP ratio, τ_{CR} is the long-run credit trend, LR is the leverage ratio, and τ_{LR} is the long-run leverage trend.[11]

Table 5 presents the results. Columns I and II show that the estimated coefficient of low volatility is negative and significant at a 5% level: prolonged periods of low volatility are followed by credit booms and excess leverage. The results are also economically meaningful: A 1% increase in low volatility is associated with a 0.73% increase in high credit and 0.63% in high leverage. On the other hand, high volatility is only 10% significant for high leverage equation, but the equality of the estimated coefficients of high and low are not rejected at a 5% level.

In their study of the predictive power of credit expansion on bank equity crashes, Baron and Xiong (2016) find that the predictive power of credit expansion is especially strong when the dividend yield is low and low dividend yield is associated with optimism. The dividend yield is found to be correlated with stock price volatility (Baskin, 1989), and hence during long-lasting periods of low volatility, overvalued asset prices may imply lower dividend yields.

[11] The HP filter is used to extract the trend. The Basel Committee's 2010 consultative document considers a range of values for the smoothing parameter for the credit gap. We opt for its median value of $\lambda = 100$. The same smoothing parameter is used to estimate the leverage trend.

To examine whether low volatility still has a significant predictive power under the presence of low dividend yields, we run (5), while including high and low dividend yields—calculated analogously to high and low volatility—as additional control variables. We obtain dividend yield data from GFD for 35 countries of the BIS sample, spanning the same sample period. Columns III and IV of Table 5 reveal that low dividend yield predicts credit booms but not financial sector leverage. The economic impact of low volatility on credit booms is substantially higher than that of low dividend yield: a 1% decrease in volatility and dividend yield below their trend translates into 0.56% and 0.21% increase in excessive lending, respectively.

The increase in financial sector leverage after periods of low volatility may be the result of increased lending in such periods as loans constitute one of the most important components of assets for commercial banks. Hence, in the last column, we include average credit of the past five years as a control variable and find that even controlling for the level of aggregate credit, low volatility increases bank leverage, consistent with low volatility enabling banks to invest in riskier securities.

In the Web Appendix, Table A.2, we provide further analysis to address concerns regarding the censored dependent variable. We show that Honore's (1992) panel Tobit estimator (with and without time dummies), Tobit regressions with random effects, and the standard least squares with fixed effects yield qualitatively similar results.

We further explore other datasets and different definitions of excessive lending and leverage to examine the sensitivity of our findings in Table A.3 in the Web Appendix. First, we use Schularick and Taylor's (2012) dataset of annual aggregate bank loans as a ratio to GDP from 1870 for 14 developed countries. Here, we have the benefit of testing excess credit mechanism by using a fairly long historical data but covering only a few countries, in contrast to the BIS data, which is cross-sectionally more comprehensive but shorter in time. Total loans are defined as the end-of-year amount of outstanding domestic currency lending by domestic banks to domestic households and nonfinancial corporations (excluding lending within the financial system).

Then, we change the definition of excessive credit and leverage. First, following the Basel Committee on Banking Supervision, we proxy credit expansion with credit-to-GDP ratio gap (defined as the difference between credit to GDP ratio and trend). Leverage expansion is proxied analogously. We find that irrespective of the definition and dataset used, low volatility remained significant. Hence, we find strong support that low levels of financial volatility are followed by credit booms and higher leverage, supporting Minsky's instability hypothesis.

5 Robustness

In order to ascertain the robustness of our results to alternative specifications, we implement nine different robustness tests, focusing on sub-samples, different models and data.

First, we examine different ways of measuring high and low volatility. One possible alternative is the deviation from a mean rather than a trend. We calculate the average historical volatility using 10 years of moving windows and then obtain high and low volatility analogously as in (2).

As we use the magnitude of deviation, our methodology effectively assigns different weights to extremely low volatility and slightly marginal deviations of volatility from its trend. However, one can still define high and low volatility based on a threshold and consider only large deviations. To this end, we calculate volatility that corresponds to large positive and negative fluctuations in a one-standard deviation band.

Hamilton (2017) raises concern about the use of an HP filter, so we examine the robustness of our findings by using the linear projection method proposed by Hamilton (2017). We estimate the trend by running an autoregressive model at the country level, where the lags of the process are selected through a AIC criteria.

Second, stock market volatility is expected to be related to macroeconomic factors (see e.g., Engle and Rangel, 2008). Hence, one can argue that unusual levels of volatility in the market returns may be manifesting unusual economic conditions that might lead to a banking crisis rather than unusual volatility. To show that low volatility is a predictor of banking crises beyond the macroeconomic and political environment, we run the HP filter in a parallel way for all of the control variables and include high and low counterparts of the variables as regressors.

Third, Baron and Xiong (2016) show that the forecasting power of credit expansion over bank equity is stronger when dividend yields are low. To check whether the predictive power of low volatility is captured by low dividend yield, we include high and low dividend yield in the baseline specification, calculated analogously to high and low volatility. Dividend yield data is obtained from GFD covering 54 countries. The earliest data point is 1855 for France. On average, we have 43 years of dividend yield observations.

Fourth, we check whether our findings are sensitive to the definition of volatility. In the baseline specification, we calculate annual volatility as the standard deviation of 12 monthly mid-year (July to June) returns. We first test the results when volatility is calculated by using monthly returns up to December. In addition, we measure volatility as the sum of absolute monthly returns, instead of standard deviation. Finally, we calculate conditional volatility using a GARCH(1,1) framework. After calculating monthly GARCH volatilities, we use the average volatility corresponding to a given year as annual volatility estimate.

Fifth, we examine whether the empirical methodology and model specification matters. We re-run regressions without any time-series and cross-sectional fixed effects, using 5-year fixed effects instead of decade fixed effects, and report the estimates from OLS regressions. We then investigate whether our results are sensitive to the exclusion of the lagged dependent variable and inclusion of the volatility trend (τ) estimated through the HP filter in the baseline specification.

Sixth, we include the level of real interest rates and the credit-to-GDP ratio gap in order to control for easy economic conditions. Data on interest rates and credit is taken from the BIS for 37 countries from 1960s. As our study takes an historical perspective, we left the inclusion of these variables as a robustness check.

Seventh, we check whether our results are robust to the chosen λ parameter. We consider λ =100, 1000, and 10000, but as the results are qualitatively similar, only the estimated coefficients for $\lambda = 100$ are reported.

Eighth, we test the sensitivity of our findings by considering alternative crisis chronologies. Although the sample of Reinhart and Rogoff (2009) is the most comprehensive for a large sample of countries over time, its accuracy has been questioned (e.g., Romer and Romer, 2015). Hence, we merged the databases of Bordo et al. (2001); Laeven and Valencia (2008); Gourinchas and Obstfeld (2012); Schularick and Taylor (2012) with that of Reinhart and Rogoff (2009) for banking by using consistent definitions of crises.[12]

The results are reported in Table 6. Although we use the full set of control variables that we used in Table 3, to conserve space we report the coefficients on high and low volatility only. See Table A.4 in the Web Appendix for an unabridged version of the table. Overall, we find that the results are qualitatively unaltered under the various robustness checks. There are small changes in specific parameter values, but the main conclusions of the importance of low volatility hold up.

Finally, we investigate the robustness of the results to specific time periods and correlations of banking crises across time and countries. We start estimating the baseline specification (3) in three key sub-periods: pre-modern finance (1800–1913), post-war (1946–2010), and the Great Moderation (1985–2006). Table 7 presents the results. In

[12]In addition, we implement the alternate set of banking crisis data of Romer and Romer (2015). As their database includes only 24 OECD countries from 1967 to 2006, more than half of the countries and almost the entire first half of the sample have no crisis. Hence, not surprisingly, we find no statistically significant relationship between volatility and financial crises. We further re-run the regressions using Reinhart and Rogoff (2009) dataset for the same countries and sample period of Romer and Romer (2015), and find consistent insignificant relationship (note that using the same 24 countries but the full sample period, i.e., from 1800 to 2010, yields qualitatively similar results to our main findings). These results underline the importance of using a sample that has rich both cross-sectional and time-series dimensions in order to examine the long-run relationship between volatility and crisis, because otherwise we run into the danger of fitting the results to the high crisis frequency or the low crisis frequency periods only.

the pre-modern period, neither high nor low volatility is significantly related to banking crises. This is not surprising, as stock markets played a much smaller role in economic activity in the early period than later would be and only the wealthiest economic agents invested in them. Similarly, the relative importance of listed firms is lower during the early sample period and the vast majority of banks are partnerships. Finally, as agriculture was a dominant economic activity, banking crises in the 19th century had stronger connection to commodity prices and partnership based firms, explaining why we fail to find a strong connection between stock market crises and banking crises in the first part of the sample. Stock markets become a much more central vehicle for financing economic activity after World War I, and especially World War II, with the general public investing in equities on a large scale, while banks became limited liability corporations. This creates a stronger relationship between stock markets and the banking sector. Both high and low volatilities predict crises during the postwar era. There is a natural breaking point in the mid-1980s marking the start of the Great Moderation, when we find strong support for low volatility predicting crises, but not high volatility.

We then split the sample into developed and emerging economies, based on the IMF definition. Column V of Table 7 shows that the economic impact of low volatility is higher for developed countries compared to the emerging ones, suggesting that engaging in risk-taking activities is more likely in developed financial systems. Moreover, interestingly, high volatility channel is statistically significant for emerging countries only. Unusually high volatility is an important driver of agents' decisions in emerging markets, which in turn affects economic activity and the probability of a banking crisis.

Banking crises are expected to cluster. For example, while there are no banking crises during the Bretton Woods era, we see a large number around 1930 and in the early 1990s. Such clustering may increase the correlations across countries, create statistical dependence, and bias the standard errors. Hence, we further examine the effects of such episodes. In Table 7, Column VII, we exclude global and major regional crisis episodes: The Great Depression (1929–1935), the Global Financial Crisis (2007–2010), World Wars (1914–1918, 1939–1945), the Latin American Debt Crisis (1978–1985) the Early 1990s recessions (1987–1992) and the Asian Financial Crisis (1996–1998) and find that low volatility significantly predicts crises even outside these periods. We then follow a procedure analogous to Baron and Xiong's (2016): For a given year, we first identify the countries that suffer a crisis and group the crisis events into 48 distinct episodes. We calculate the averages of the previous 5-year volatility deviations from its trend for the countries in a given episode and use them as a single observation. Table 8 lists the episodes. The results show that the average volatility deviation during the previous five years is -0.534 and significant at a 5% level, showing that, on the average, volatility preceding a crisis is statistically negative, consistent with our main findings.

6 Conclusion

In this paper, we create an extensive dataset of financial market volatility, spanning 60 countries and up to 211 years. This data is used to investigate the relationship between volatility and financial crises via a two-way fixed effects dynamic panel-logit analysis. We further decompose volatility into high and low deviations from its trend to investigate theoretical predictions that emphasize the effects high or low volatility on agents' decisions.

Our main contribution is to show that low volatility is a strong predictor of financial crises. Low volatility over a prolonged period leads to higher risk-taking, measured as high credit-to-GDP and financial sector leverage. Low volatility induces risk-taking, which leads to riskier investments. Over time, loan losses mount, causing problems for banks, which may eventually culminate in a crisis.

The results support the early theoretical predictions that financial market risk affects economic decisions, especially when it deviates from what economic agents have come to expect and reinforces the current literature on the determinants of financial crises.

Our findings should be of value to macroprudential and monetary policy policymakers, as they provide guidance on how one should think about the relationship between financial market risk and the stability of the financial system and suggest that low volatility could be used as an early warning indicator.

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Table 1: Sample details
This table lists the countries in our sample, whether they are developed or emerging markets based on the IMF classification, sample coverage, and the names of the market indexes. Source: Global Financial Data.[13]

Country	Classification	Coverage	Market Index
Argentina	Emerging	Jan 1947–Jun 1958 /	Argentina Swan, Culbertson and Fritz Index /
		Dec 1966–Dec 2010	Buenos Aires SE General Index (IVBNG)
Australia	Developed	Jan 1875–Dec 2010	Australia ASX All-Ordinaries
Austria	Developed	Jan 1922–Dec 2010	Austria Wiener Boersekammer Share Index (WBKI)
Belgium	Developed	Jan 1897–Dec 2010	Brussels All-Share Price Index
Bolivia	Emerging	Jan 2004–Mar 2014	Bolivia Stock Market Capitalization
Brazil	Emerging	Jan 1955–Feb 1993 /	Rio de Janeiro Bolsa de Valores Index (IBV) /
		Apr 1993–Dec 2010	BOVESPA
Canada	Developed	Jan 1915–Dec 2010	Canada S&P/TSX 300 Composite
Chile	Emerging	Jan 1927–Dec 2010	Santiago SE Indice General de Precios de Acciones (IGPA)
China	Emerging	Jan 1991–Dec 2010	Shanghai SE Composite
Colombia	Emerging	Jan 1927–Dec 2010	Colombia IGBC General Index
Costa Rica	Emerging	Jan 1995–Dec 2010	Costa Rica Bolsa Nacional de Valores Index
Cote Divoire	Emerging	Jan 1996–Dec 2010	Cote d'Ivoire Stock Market Index
Denmark	Developed	Jan 1921–Dec 2010	OMX Copenhagen All-Share Price Index
Ecuador	Emerging	Jan 1994–Dec 2010	Ecuador Bolsa de Valores de Guayaquil
Egypt	Emerging	Jan 1950–Sep 1962 /	Egyptian SE Index /
		Dec 1992–Dec 2010	Cairo SE EFG General Index
Finland	Developed	Jan 1920–Dec 2010	OMX Helsinki All-Share Price Index
France	Developed	Jan 1840–Dec 2010	France CAC All-Tradable Index
Germany	Developed	Jan 1870–Dec 2010	Germany CDAX Composite Index
Ghana	Emerging	Dec 1990–Oct 2010	Ghana SE Databank Index /
			Ghana SE Composite Index
Greece	Developed	Jul 1929–Sep 1940 /	Greece Stock Market Index /
		Dec 1952–Dec 2010	Athens SE General Index
Hungary	Emerging	Dec 1924–Mar 1948 /	Hungary Stock Market Index /
		May 2002–Dec 2010	OETEB Hungary Traded Index
Iceland	Developed	Jan 1993–Dec 2010	OMX Iceland All-Share Price Index
India	Emerging	Jul 1922–Dec 2010	Bombay SE Sensitive Index
Indonesia	Emerging	Apr 1983–Dec 2010	Jakarta SE Composite Index
Ireland	Developed	Jan 1934–Dec 2010	Ireland ISEQ Overall Price Index
Italy	Developed	Oct 1905–Dec 2010	Banca Commerciale Italiana Index
Japan	Developed	Aug 1914–Dec 2010	Tokyo SE Price Index (TOPIX)
Kenya	Emerging	Jan 1964–Dec 2010	Nairobi SE Index
Korea	Developed	Jan 1962–Dec 2010	Korea SE Stock Price Index (KOSPI)
Malaysia	Emerging	Jan 1974–Dec 2010	Malaysia KLSE Composite
Mauritius	Emerging	Aug 1989–Dec 2010	Securities Exchange of Mauritius Index (SEMDEX)

[13]We report the name of the market index used at the end of the sample period. Given the long historical data, it is not possible to list all of the indexes used for all countries. For example, for the U.S., price data until 1870 is taken from Macaulay (1938), where the indexes are created based on stock prices of banks, insurance companies, and rail roads. Beginning in 1871, the Cowles Commission's back-calculated composite index of stocks is used. Finally, after 1923, S&P index is used. See GFD for details.

Table 1: Sample details (cont.)

Country	Classification	Coverage	Market Index
Mexico	Emerging	Jan 1931–Dec 2010	Mexico SE Indice de Precios y Cotizaciones (IPC)
Morocco	Emerging	Jan 1988–Dec 2010	Casablanca Financial Group 25 Share Index
Netherlands	Developed	Jan 1919–Dec 2010	Netherlands All-Share Price Index
New Zealand	Developed	Jan 1931–Dec 2010	New Zealand SE All-Share Capital Index
Nigeria	Emerging	Jan 1988–Dec 2010	Nigeria SE Index
Norway	Developed	Jan 1914–Dec 2010	Oslo SE OBX-25 Stock Index
Panama	Emerging	Jan 1993–Dec 2010	Panama SE Index (BVPSI)
Peru	Emerging	Jan 1933–Dec 2010	Lima SE General Index
Philippines	Emerging	Jan 1953–Dec 2010	Manila SE Composite Index
Poland	Emerging	May 1994–Dec 2010	Warsaw SE 20-Share Composite
Portugal	Developed	Jan 1933–Dec 2010	Oporto PSI-20 Index
Romania	Emerging	Jun 1998–Dec 2010	Bucharest SE Composite Index
Russia	Emerging	Oct 1993–Dec 2010	Russia AK&M Composite (50 shares)
Singapore	Developed	Aug 1965–Dec 2010	Singapore FTSE Straits-Times Index
South Africa	Emerging	Jan 1910–Dec 2010	FTSE/JSE All-Share Index
Spain	Developed	Jan 1915–Dec 2010	Madrid SE General Index
Sri Lanka	Emerging	Jan 1985–Dec 2010	Colombo SE All-Share Index
Sweden	Developed	Jan 1906–Dec 2010	Sweden OMX Affrsvrldens General Index
Switzerland	Developed	Jan 1916–Dec 2010	Switzerland Price Index
Taiwan	Developed	Jan 1967–Dec 2010	Taiwan SE Capitalization Weighted Index
Thailand	Emerging	May 1975–Dec 2010	Thailand SET General Index
Tunisia	Emerging	Jan 1998–Dec 2010	Tunisia SE Index
Turkey	Emerging	Jan 1986–Dec 2010	Istanbul SE IMKB-100 Price Index
United Kingdom	Developed	Jan 1800–Dec 2010	UK FTSE All-Share Index
United States	Developed	Jan 1800–Dec 2010	S&P 500 Composite Price Index
Uruguay	Emerging	Jan 1925–Dec 1995 /	Uruguay SE Index /
		Jan 2008–Dec 2010	Bolsa de Valores de Montevideo Index
Venezuela	Emerging	Jan 1937–Dec 2010	Caracas SE General Index
Zambia	Emerging	Jan 1997–Aug 2007	Zambia Lusaka All-Share Index (LASI)
Zimbabwe	Emerging	Jan 1969–Dec 2010	Zimbabwe Industrials Index

Table 2: Descriptive analysis

This table shows time-series averages of each variable indicated by the column headers for the period from 1800–2010. We present the average mean, median, and standard deviation for developed countries, emerging countries, and the whole sample. σ is the annual volatility level (scaled by $\sqrt{12}$), δ^{high} and δ^{low} are high and low volatility introduced in (2), $\mathbb{P}$(crisis) is the probability that a country enters into a new crisis. It is calculated as the number of crisis divided by the available sample period. Crisis is the dummy variable that takes 1 at the beginning year of a crisis, obtained from Reinhart and Rogoff (2009), $\log GDP$ is the natural logarithm of the GDP per capita, $\Delta PD/GDP$ is the change in public-debt-to-GDP ratio, $POLCOMP$ is the degree of political competition, and $INFLATION$ is the annual inflation rate. All of the figures are reported in percentage terms. ***, **, and * denote the significance levels at the 1%, 5%, and 10%, respectively, for the sample mean comparison tests corresponding to the variables between emerging and developed countries.

Variable	σ I	δ^{high} II	δ^{low} III	$\mathbb{P}$(crisis) IV	$\log GDP$ V	$\Delta PD/GDP$ VI	$POLCOMP$ VII	$INFLATION$ VIII
Emerging countries								
Mean	23.39***	4.11**	-3.54**	2.45***	7.62***	0.14	5.18***	12***
Median	20.26	3.27	-2.93	2.17	7.58	0.03	5.06	9.54
Standard deviation	10.58	3.29	2.93	1.42	0.55	3.35	2.02	8.2
Developed countries								
Mean	16.07	2.77	-2.44	3.51	8.31	0.23	6.89	4.54
Median	15.04	2.12	-1.85	3.32	8.36	0.16	6.55	3.14
Standard deviation	4.7	1.3	1.48	1.47	0.35	0.76	1.98	3.27
Whole sample								
Mean	20.34	3.53	-3.06	2.89	7.9	0.18	5.88	8.89
Median	17.55	3	-2.26	2.84	7.96	0.08	5.81	6.72
Standard deviation	9.31	2.69	2.46	1.52	0.58	2.59	2.16	7.54

Table 3: Volatility and financial crises

This table presents the results for the regression equation introduced in (3). The dependent variable is a dummy variable that takes the value 1 in the first year of a banking crisis. δ^{high} and δ^{low} are high and low volatility introduced in (2). σ is the volatility level, τ is the trend of volatility obtained from the HP filter, $\log GDP$ is the natural logarithm of the GDP per capita, $\Delta PD/GDP$ is the change in public-debt-to-GDP ratio, $POLCOMP$ is the degree of political competition, and $INFLATION$ is the annual inflation rate. Past five year averages of the explanatory variables are used in the regressions. All of the specifications include region and decade fixed effects. For the sake of brevity, the estimated coefficients of fixed effects are omitted. The panel covers 60 countries and spans 1800–2010. The standard errors, reported in parentheses, are robust and dually clustered at the year and country level. The last two rows report the p-values corresponding to the hypotheses tests listed.

Dep. Var.: $C_{i,t}^{\text{Banking}}$	I	II	III	IV	V	VI
$\sigma_{i,t-1 \text{ to } t-5}$	0.08***	-0.02				
	(0.029)	(0.049)				
$\lvert\sigma-\tau\rvert_{i,t-1 \text{ to } t-5}$			0.26***	0.26***		
			(0.084)	(0.100)		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$					0.23**	0.20
					(0.113)	(0.128)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$					-0.29***	-0.31***
					(0.098)	(0.115)
$C_{i,t-1 \text{ to } t-5}$	-7.07***	-7.42***	-7.41***	-7.78***	-7.46***	-7.86***
	(1.491)	(1.510)	(2.006)	(2.051)	(2.026)	(2.039)
$\log GDP_{i,t-1 \text{ to } t-5}$		-0.04		0.09		0.07
		(0.198)		(0.229)		(0.229)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$		-0.05**		-0.07**		-0.07***
		(0.022)		(0.031)		(0.026)
$POLCOMP_{i,t-1 \text{ to } t-5}$		-0.07		-0.09**		-0.09*
		(0.046)		(0.043)		(0.048)
$INFLATION_{i,t-1 \text{ to } t-5}$		0.03***		0.02		0.02
		(0.011)		(0.011)		(0.011)
Num of Obs.	3,037	2,850	2,211	2,134	2,211	2,134
Pseudo R^2	0.101	0.121	0.082	0.105	0.082	0.106
Marginal effects (%)						
$\sigma_{i,t-1 \text{ to } t-5}$	0.224	-0.041				
$\lvert\sigma_{i,t-1 \text{ to } t-5}-\tau_{i,t-1 \text{ to } t-5}\rvert$			0.969	0.849		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$					0.844	0.659
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$					-1.084	-1.011
p-values						
$H_0^a : \text{ME}_{\delta^{\text{high}}} = \text{ME}_{\delta^{\text{low}}}$					0.0001	0.0015
$H_0^b : \lvert\text{ME}_{\delta^{\text{high}}}\rvert = \lvert\text{ME}_{\delta^{\text{low}}}\rvert$					0.5283	0.3795

Table 4: Volatility and financial crises: different lag lengths

This table presents the results for the regression equation introduced in (3) for $L = 1, 2, ..., 11$. The dependent variable is a dummy variable that takes the value 1 in the first year of a banking crisis. δ^{high} and δ^{low} are high and low volatility introduced in (2). Control variables are introduced in Table 3. All of the specifications include region and decade fixed effects. For the sake of brevity, the estimated coefficients of fixed effects are omitted. The panel covers 60 countries and spans 1800–2010. The standard errors, reported in parentheses, are robust and dually clustered at the year and country level. The last two rows report the p-values corresponding to the hypotheses tests listed.

Dep. Var.: $C^{\text{Banking}}_{i,t}$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	.	$L=9$	$L=10$	$L=11$
$\delta^{\text{high}}_{i,t-1 \text{ to } t-L}$	-0.01	0.03	0.12	0.14	0.20	.	0.19	0.17	0.12
	(0.083)	(0.116)	(0.112)	(0.132)	(0.128)	.	(0.163)	(0.176)	(0.192)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-L}$	-0.16**	-0.19**	-0.23**	-0.27***	-0.31***	.	-0.28**	-0.24*	-0.22
	(0.064)	(0.079)	(0.104)	(0.104)	(0.115)	.	(0.134)	(0.141)	(0.137)
$C_{i,t-1 \text{ to } t-L}$		-3.89***	-5.30***	-6.97***	-7.86***	.	-11.62***	-10.19***	-10.90***
		(1.148)	(1.558)	(1.571)	(2.039)	.	(2.049)	(1.837)	(1.956)
$\log GDP_{i,t-1 \text{ to } t-L}$	0.09	0.05	0.07	0.07	0.07	.	-0.00	-0.02	-0.04
	(0.147)	(0.165)	(0.194)	(0.219)	(0.229)	.	(0.256)	(0.249)	(0.252)
$\Delta PD/GDP_{i,t-1 \text{ to } t-L}$	-0.01	-0.02	-0.04**	-0.05	-0.07***	.	-0.09*	-0.10*	-0.13**
	(0.010)	(0.016)	(0.021)	(0.034)	(0.026)	.	(0.055)	(0.055)	(0.051)
$POLCOMP_{i,t-1 \text{ to } t-L}$	-0.09**	-0.08**	-0.09**	-0.09**	-0.09*	.	-0.09**	-0.08*	-0.08**
	(0.040)	(0.041)	(0.043)	(0.043)	(0.048)	.	(0.044)	(0.044)	(0.039)
$INFLATION_{i,t-1 \text{ to } t-L}$	0.01	0.01	0.01	0.02	0.02	.	0.02	0.02	0.02*
	(0.007)	(0.008)	(0.009)	(0.011)	(0.011)	.	(0.012)	(0.012)	(0.011)
Num of Obs.	1,946	2,085	2,108	2,124	2,134	.	2,168	2,175	2,183
Pseudo R^2	0.0656	0.0834	0.0916	0.0998	0.106		0.102	0.0880	0.0899
Marginal effects (%)									
$\delta^{\text{high}}_{i,t-1 \text{ to } t-L}$	-0.042	0.097	0.407	0.475	0.659	.	0.634	0.579	0.432
$\delta^{\text{low}}_{i,t-1 \text{ to } t-L}$	-0.644	-0.677	-0.801	-0.923	-1.011	.	-0.939	-0.839	-0.751
p-values									
$H_0^a: \text{ME}_{\delta^{\text{high}}} = \text{ME}_{\delta^{\text{low}}}$	0.1710	0.1139	0.0130	0.0069	0.0015		0.0260	0.0641	0.1251
$H_0^b: \lvert\text{ME}_{\delta^{\text{high}}}\rvert = \lvert\text{ME}_{\delta^{\text{low}}}\rvert$	0.1710	0.1099	0.2700	0.2448	0.3795		0.5596	0.6397	0.5687

Table 5: Low volatility and risk-taking

The table presents the results for the regression equation introduced in (5) for $L = 5$. The dependent variable used is listed at the column header. $\delta^{\text{high}}_{\text{CR}\ i,t}$ and $\delta^{\text{high}}_{\text{LR}\ i,t}$ are high credit and high leverage defined in (6) and (7), respectively. HP filter with a smoothing parameter of 100 is used to calculate the gap variables. δ^{high} and δ^{low} are high and low volatility introduced in (2). $dy^{\text{high}}_{i,t-1 \text{ to } t-5}$ and $dy^{\text{low}}_{i,t-1 \text{ to } t-5}$ are high and low dividend yields, respectively, defined analogously to high and low volatility. We obtain dividend yield data from Global Financial Data. $INTRATE$ is the real interest rate. The rest of the variables are introduced in Table 3. Credit-to-GDP data is obtained from BIS and leverage data is obtained from Lee et al. (2017). Region and decade fixed effects are included in all of the specifications. For the sake of brevity, the estimated coefficients of fixed effects are omitted. The standard errors, reported in parentheses, are robust and dually clustered at the year and country level. The last two rows report the p-values corresponding to the hypotheses tests listed.

$Y_{i,t}$	$Y_{i,t} = \delta^{\text{high}}_{\text{CR}\ i,t}$ I	$Y_{i,t} = \delta^{\text{high}}_{\text{LR}\ i,t}$ II	$Y_{i,t} = \delta^{\text{high}}_{\text{CR}\ i,t}$ III	$Y_{i,t} = \delta^{\text{high}}_{\text{LR}\ i,t}$ IV	$Y_{i,t} = \delta^{\text{high}}_{\text{LR}\ i,t}$ V
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$	-0.28	0.44*	-0.21	0.57	0.44*
	(0.989)	(0.224)	(1.309)	(0.356)	(0.225)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$	-2.64***	-0.59***	-2.39***	-0.54*	-0.57**
	(0.778)	(0.218)	(0.809)	(0.272)	(0.225)
$dy^{\text{high}}_{i,t-1 \text{ to } t-5}$			0.09	-0.42	
			(0.076)	(0.335)	
$dy^{\text{low}}_{i,t-1 \text{ to } t-5}$			-0.10**	-0.81	
			(0.044)	(1.340)	
$CR_{i,t-1 \text{ to } t-5}$					-0.00
					(0.001)
$Y_{i,t-1 \text{ to } t-5}$	0.62***	0.49***	0.63***	0.27	0.49***
	(0.132)	(0.147)	(0.170)	(0.258)	(0.155)
$\log GDP_{i,t-1 \text{ to } t-5}$	0.62	1.07	1.49	0.84	1.12
	(2.190)	(0.795)	(2.353)	(0.642)	(0.798)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$	-0.70***	0.08	-0.73***	-0.04	0.08
	(0.183)	(0.065)	(0.237)	(0.068)	(0.066)
$POLCOMP_{i,t-1 \text{ to } t-5}$	0.26	0.07*	0.40	0.20***	0.08
	(0.311)	(0.039)	(0.295)	(0.066)	(0.060)
$INFLATION_{i,t-1 \text{ to } t-5}$	-0.18	0.06	-0.07	-0.16	0.05
	(0.179)	(0.219)	(0.261)	(0.443)	(0.222)
$INTRATE_{i,t-1 \text{ to } t-5}$	0.01	0.00	-0.07	-0.00	0.00
	(0.175)	(0.020)	(0.208)	(0.031)	(0.019)
Observations	875	118	723	96	118
adjR^2	0.274	0.225	0.283	0.0452	0.218
p-values					
$H_0^a : \text{ME}_{\delta^{\text{high}}} = \text{ME}_{\delta^{\text{low}}}$	0.1195	0.0134	0.2311	0.0716	0.0158
$H_0^b : \lvert\text{ME}_{\delta^{\text{high}}}\rvert = \lvert\text{ME}_{\delta^{\text{low}}}\rvert$	0.1195	0.3849	0.2311	0.8377	0.4552

Table 6: Robustness: Volatility and financial crises
This table presents the results for the robustness analysis. The dependent variable is a dummy variable that takes the value 1 in the first year of a banking crisis. In Column I, high and low volatility are defined as the deviation of volatility level from its historical mean calculated as the average volatility during the past ten years. In Column II, high and low volatility are defined as the deviation of volatility level from a one standard deviation band. In column III, we employ the method proposed by Hamilton (2017) instead of the HP filter to estimate the trend. In Column IV, we include high and low counterparts of the control variables, all defined analogously to high and low volatility. Similarly in Column V, we include high and low dividend yield as regressor. In Column VI, volatility is calculated by employing monthly returns up to December (end year) instead of mid-year returns. In Column VII, we measure volatility as the sum of absolute monthly returns and in Column VIII, we calculate annual volatility using a GARCH(1,1) framework. In Column IX, we repeat the analysis without any fixed effects. In Column X, we report the results from the OLS regressions. In Column XI, we present the results when the lag of the dependent variable is excluded. In Column XII, we include the trend (τ) estimated through an HP filter in the regression along with high and low volatility variables. In Columns XIII and XIV, we include the interest rate and credit-to-GDP gap as control variables, respectively. In Column XV, we report the results when the smoothing parameter of the HP filter is set to 100 instead of 5000. Finally, in Column XVI, we report the results when we merge the crisis database of Reinhart and Rogoff (2009) with that of Bordo et al. (2001); Laeven and Valencia (2008); Gourinchas and Obstfeld (2012); Schularick and Taylor (2012). All of the control variables introduced in Table 3 are included in the specifications but not presented for the sake of brevity. The panel covers 60 countries and spans 1800–2010. The standard errors, reported in parentheses, are robust and dually clustered at the year and country level. See the Web Appendix Table A.4 for the unabridged version of the table.

Dep. Var.: $C_{i,t}^{\text{Banking}}$	Historical Mean I	Band II	Hamilton III	High/low Macro vars IV	High/low dividends V	12M VI	ABS VII	GARCH VIII
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.16*	0.22*	-0.04	0.35**	0.13	0.08	0.21	0.32**
	(0.089)	(0.126)	(0.156)	(0.160)	(0.171)	(0.129)	(0.162)	(0.159)
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	-0.30***	-0.50**	-0.03***	-0.42**	-0.44**	-0.21**	-0.35**	-0.61***
	(0.115)	(0.209)	(0.009)	(0.193)	(0.174)	(0.103)	(0.144)	(0.192)
Num of Obs.	2.158	2.155	2.247	1,976	1,248	2,181	2,134	1,618
Pseudo R^2/adjR^2	0.103	0.104	0.0976	0.108	0.101	0.102	0.105	0.123

Dep. Var.: $C_{i,t}^{\text{Banking}}$	No FEs IX	OLS X	No lagged Dep. Var. XI	Trend Included XII	Int. Rates Included XIII	Credit Included XIV	$\lambda = 100$ XV	Merged Data XVI
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.15	0.01	0.14	0.23	0.35	0.31	0.04	0.19
	(0.105)	(0.006)	(0.131)	(0.151)	(0.226)	(0.261)	(0.178)	(0.131)
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	-0.24**	-0.01**	-0.22**	-0.41**	-0.48***	-0.51***	-0.37**	-0.30**
	(0.094)	(0.006)	(0.099)	(0.206)	(0.154)	(0.137)	(0.184)	(0.118)
Num of Obs.	2,886	2,886	2,134	2,134	1,205	1,047	2,134	2,134
Pseudo R^2/adjR^2	0.0292	0.0410	0.0665	0.107	0.123	0.114	0.103	0.111

Table 7: Volatility and financial crises: sub-samples

This table presents the results for the regression equation introduced in (3) for different sub-periods and geographical subsets. The early (1800–1913), postwar (1946–2010), and Great Moderation (1985–2006) periods are considered. In Columns V and VI, we report the estimated coefficients for developed and emerging countries, respectively. Finally in Column VII, we exclude the periods corresponding to six major historical episodes (the Great Depression, World Wars, the Early 1990s recessions, the Latin American Debt Crisis, the Asian Financial Crisis, and the Global Financial Crisis). The dependent variable is a dummy variable that takes the value 1 in the first year of a banking crisis. δ^{high} and δ^{low} are high and low volatility introduced in (2). All of the control variables are defined in Table 3. Past five year averages of the explanatory variables are used in the regressions. Region and decade fixed effects used in the specifications. For the sake of brevity, the estimated coefficients of fixed effects are omitted. The standard errors, reported in parentheses, are robust and dually clustered at the year and country level.

Dep. Var.: $C_{i,t}^{\text{Banking}}$	Whole sample I	Early Period II	Post-war III	Great Mod. IV	Developed V	Emerging VI	Crises Removed VII
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.20	-0.76	0.27**	0.10	0.07	0.38**	0.30*
	(0.128)	(0.499)	(0.129)	(0.231)	(0.235)	(0.161)	(0.158)
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	-0.31***	0.86	-0.30**	-0.35***	-0.40**	-0.35**	-0.39**
	(0.115)	(0.742)	(0.123)	(0.128)	(0.168)	(0.146)	(0.172)
$C_{i,t-1 \text{ to } t-5}$	-7.86***	-11.58***	-7.46**	-5.75*	-7.48***	-10.48**	-10.54***
	(2.039)	(1.515)	(3.129)	(3.189)	-1918	-4971	(2.339)
$logGDP_{i,t-1 \text{ to } t-5}$	0.07	2.64	0.26	-0.10	-0.10	0.48**	0.58
	(0.229)	(4.882)	(0.303)	(0.271)	(0.413)	(0.212)	(0.427)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$	-0.07***	-0.14**	-0.06***	-0.06	-0.12***	-0.05	-0.04
	(0.026)	(0.071)	(0.023)	(0.060)	(0.042)	(0.053)	(0.025)
$POLCOMP_{i,t-1 \text{ to } t-5}$	-0.09*	0.14	-0.11*	0.03	-0.03	-0.13	-0.08*
	(0.048)	(0.283)	(0.060)	(0.172)	(0.057)	(0.106)	(0.045)
$INFLATION_{i,t-1 \text{ to } t-5}$	0.02	0.03	0.01	0.02	0.03	0.01	0.03**
	(0.011)	(0.109)	(0.009)	(0.012)	(0.040)	(0.012)	(0.014)
Num of Obs.	2,134	239	1,595	819	1.459	644	946
Pseudo R^2	0.106	0.163	0.100	0.150	0.096	0.220	0.191
Marginal effects (%)							
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.659	-3.092	0.770	0.196	0,253	0,651	0.618
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	-1.011	3.519	-0.877	-0.661	-1,400	-0,596	-0.810

Table 8: Clustering banking crisis

This table presents banking crisis events grouped into 48 distinct historical episodes (e.g, Great Depression, Latin American Debt Crisis, Asian Financial Crisis, Global Financial Crisis) and the previous 5-year averages of volatility deviation. For each year, we first identify the countries that suffer a crisis. For those countries, we calculate the average of the deviation of volatility with respect to its trend $(\sigma - \tau)$ over the previous 5 years of the crisis event. Then, we group the crisis events into episodes and calculate the time-series and cross-sectional averages of volatility deviations within the same historical episode. Finally, taking each historical episode as an independent observation, we calculate the average across the episodes and conduct a t-test.

Episode	Year	$(\sigma - \tau)_{t-1 \text{ to } t-5}$	Effected countries (ISO)	Definition of the episode
1	1810	-0.112	GBR	
2	1815	0.507	GBR	
3	1818	0.230	USA	
4	1825	-0.032	GBR, USA	Panic of 1825
5	1836	-0.016	GBR, USA	
6	1847	-0.438	GBR	Panic of 1847
7	1857	-0.332	GBR, USA	Panic of 1857
8	1866	0.632	GBR	The Overend Gurney crisis
9	1873	-1.377	USA	Panic of 1873 and the Long Depression
10	1884	0.338	USA	Panic of 1884
11	1890	0.169	GBR, USA, DEU	The Baring crisis
12	1893	0.061	USA	Panic of 1893
13	1901	0.018	DEU	
14	1907	-0.419	USA	Panic of 1907
15	1914-1918	-0.257	BEL, FRA, GBR, USA	World War I
16	1922	0.742	SWE	
17	1927	-1.426	JPN	Showa Financial Crisis of 1927
18	1929-1939	-0.297	USA, FRA, ITA, AUS, BEL, CHE, DEU, ESP, FIN, NOR, SWE, NLD	Great depression
19	1947	-0.127	IND	
20	1971	2.643	URY	
21	1973-1975	0.714	GBR	Secondary banking crisis 1973–1975
22	1977	0.580	DEU	
23	1977	1.543	ESP	
24	1977	1.467	ZAF	

Table 8: Clustering banking crisis (cont.)

Episode	Year	$(\sigma - \tau)_{t-1 \text{ to } t-5}$	Effected countries (ISO)	Definition of the episode
25	1976-1983	1.292	CHL, VEN, ARG, MEX, URY, CHL, COL, PER, BRA	Latin american debt crisis
26	1981-1985	-0.596	PHL, SGP, KOR, TWN, KOR, MYS	
27	1983-1984	-0.401	CAN, GBR, USA	Early 1980s recession
28	1985	-0.865	KEN	
29	1987-1991	1.034	DNK, FIN, NOR	Scandinavian banking crisis
30	1989	-5.733	ARG	Argentina crisis
31	1989	-1.143	ZAF	The crisis of Apartheid
32	1987-1993	1.517	NZL, AUS, BRA, ITA, GBR GRC, KEN, IND, VEN	
33	1991	0.211	SWE	Swedish banking rescue
34	1992	2.432	JPN	Japanese crisis
35	1994	1.524	BRA	
36	1994	-1.130	FRA	
37	1994	-4.881	IDN	
38	1994	-3.171	MEX	Economic crisis in Mexico
39	1995	-5.027	ARG	Argentine banking crisis of 1995
40	1995	-0.230	GBR	Baring crisis
41	1995	-0.082	TWN	
42	1995	1.007	ZWE	
43	1996-1998	-1.086	THA, IDN, KOR, MYS, PHL, TWN	Asian financial crisis
44	1998	-0.701	COL	
45	1999	-7.666	PER	
46	2000	0.817	TUR	Turkish banking crisis
47	2001	-6.761	ARG	Argentine banking crisis of 2001
48	2007-2009	-0.804	GBR, IRL, ISL, USA, AUT, BEL, CHE, DEU, DNK, ESP, FRA, GRC, NLD, PRT, RUS	Global financial crisis
Average		-0.534		
p-value		0.0478		