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Learning from History: Volatility and Financial Crises*

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Abstract

We study the effects of volatility on financial crises by constructing a cross-country database spanning over 200 years. Volatility itself is not a significant predictor of banking crises, but unusually high and low volatilities are. Low volatility is followed by credit build-ups, indicating that agents take more risk in periods of low risk consistent with Minsky instability hypothesis, and increasing the likelihood of a crisis. The effect is stronger when financial markets are more prominent and less regulated. Finally, both high and low volatilities make stock market crises more likely, while volatility in any form has no impact on currency crises.

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, June 18, 2014.

Do unusual levels of financial market volatility imply an increased likelihood of a subsequent financial crisis? A common wisdom maintains it does, pointing to the low volatility in the United States in the years prior to the 2008 crisis. This view 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 (1992) instability hypothesis that 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". However, to the best of our knowledge, it has not been conclusively empirically studied, which motivates our investigation into the link between financial market volatility, risk-taking, and crises.

Financial market volatility is of clear interest to policymakers, with the above quotation by Chair Yellen just one example. Within the post-crisis macro-prudential 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 part of the macro-prudential monitoring frameworks. Unfortunately, in the absence of clear empirical guidance as how volatility affects future crises, it can be a difficult indicator to interpret.

Concerns about the relationship between the financial market and economic risk have a long history in the economic literature, notably Keynes (1936), Hayek (1960), and Minsky (1992) who argue that economic agents change their risk-taking behavior when financial market risk changes.

The theoretical literature suggests that financial market volatility affects economic decisions, especially when it deviates from what economic agents expect it to be. Relatively lower levels of volatility may lead to a crisis, via what we denote the *low volatility channel*. This is consistent with both the general equilibrium framework of Danielsson et al. (2012), whereby low risk induces economic agents to take more risk, which then endogenously affects the likelihood of future shocks, and the volatility paradox of Brunnermeier and Sannikov (2014), where low fundamental risk leads to higher equilibrium leverage, and hence the build-up of systemic risk.

High volatility may also lead to a crisis as it indicates higher uncertainty regarding future cash flows and discount rates, and hence, future economic conditions. Such high volatility can therefore be seen by forward-looking economic agents as a signal of the increased risk of adverse future outcomes and a pending crisis. We term this chain of events the *high volatility channel*.

That leaves the question of how to quantify high and low volatility. Our empirical evidence indicates that volatility exhibits a slow-moving, non-linear trend. Borrowing terminology from the literature on output gap, we interpret this slow-run trend as the long-term volatility and calculate it using a one-sided Hodrick and Prescott (1997) filter. We then calculate the "volatility gap". Relatively high and low volatility (or high and low volatility in short) are defined as the deviations of volatility from above and below its trend, respectively. This implies four different notions of volatility: the level of volatility, volatility trend, and high and low volatilities.

Several authors have examined the relationship between volatility and recessions and patterns in volatility during crises, almost exclusively focusing on the United States.[1] However, to the best of our knowledge we are the first to formally examine how volatility may predict financial crises. While we do not know why the literature has not addressed the issue, we can advance two hypotheses. First, the presence of two volatility channels is likely to frustrate empirical analysis solely focusing on the level of volatility. Second, as we argue below, it is helpful to make use of long historical relationships.

In an empirical exploration of the connection between volatility and crises we face two paths. We could focus on recent history with daily market activity measurements and ample economic and financial statistics. However, this would limit us to data from the past few decades at best. Since crises are rare events—a typical OECD member country suffers a banking crisis every 35 years—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-

[1] See for example, Schwert (1989, 1990); Hamilton and Lin (1996); Fornari and Mele (2009); Corradi et al. (2013)

term historical view believing it to be a better way to obtain meaningful relationships between volatility and crises.

We construct a database on historical volatilities from primary sources, collecting monthly returns of stock market indices from which we obtain annual volatility estimates. The sample covers 60 countries and spans 211 years, resulting in about 3700 country-year observations. On average, the database covers 62 years of historical observations per country.

Our main interest is in banking crises and we adopt the dataset of Reinhart and Rogoff (2009).[2] The end result is an unbalanced panel that contains a binary indicator of whether a banking crisis occurs in a given year and country. The coverage is fairly comprehensive, with 262 banking crises.

We obtain a number of results on the relationship between volatility, risk-taking, and crises, providing new insights while also being consistent with the extant theoretical literature. We are not aware of any empirical paper documenting most of these phenomena.

First, the level of volatility does not predict financial crises, but prolonged periods of low volatility do, with low volatility having a strong in-sample and out-of sample predictive power over crises. 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 into a 1.12% increase in the probability of a banking crisis. Moreover, 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.

In our second result, we examine in more detail how low volatility causes financial crisis. We find that low volatility is followed by credit build-up, indicating that economic agents take more risk in periods of low financial risk, which in turn endogenously increases the likelihood of future crises. These results extend the findings of Schularick and Taylor (2012), who show that credit growth predicts crises. Our findings are robust to a range

[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); Romer and Romer (2015). We obtain qualitatively similar results with using Reinhart and Rogoff (2009). Hence, for consistency purposes we opted to employ the most comprehensive database both in time-series and cross-sectional dimensions.

of tests based on alternative model specifications, sample selections, definitions of risk-taking, crises, and volatility.

Third, since our 211-year sample contains a variety of economic systems, market structures, and technological developments, it is of interest to examine the volatility–crisis relationship over key sub-periods of the sample. 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. The relationship weakened again during the Bretton Woods era when financial markets and capital flows were heavily regulated, and became especially strong since.

In our last set of results, we examine the effects of volatility on stock market and currency crises. For the former, both high and low volatility are important. The high volatility channel is most important closer to a crisis, while the low channel is most important farther from a crisis. Low volatility Granger-causes high volatility, but not vice versa, further supporting the view that low volatility induces risk-taking, which only materializes during a crisis, while high volatility is a signal of a pending crisis. Finally, volatility–of any form–does not have an impact on currency crises.

Taken together, we find unambiguous support for volatility increasing the likelihood of financial crises. Volatility itself does not predict crises, and we surmise that is because the level of volatility varies over time and countries: what would be a high level of volatility in one country or time period could be low in another. It is necessary to decompose volatility into high and low volatilities, and when doing so, we find strong support that low volatility that lasted up to 10 years predicts crises, where the effect is the strongest when volatility stays low for at least five years. The volatility–crises relationship becomes more pronounced when financial markets are more prominent and less regulated.

These results should be of value to macro-prudential and monetary policymakers, as they provide clear guidance for how one should think about the relationship between financial market risk and the macroeconomy. By identifying the channels by which volatility affects the incidence of crises, policymakers are able to better understand the links between the two. Hence, they may want to consider including high and low volatilities in their set of crisis indicators, which would lead to more robust policy tools dealing with financial stability and systemic events.

The rest of the paper is organized as follows. In Section 2, we explain the high and low volatility channels and their possible relationship with financial crises in detail, along with the related literature. In Section 3, we describe the construction of the database and the method to decompose volatility. In Sections 4 and 5, we present the econometric methodology and the results, respectively. Finally, Section 6 concludes.

2 Background and related literature

Financial market risk directly affects the real economy because of its role in financing economic projects and its impact on agents' expectations. Not surprisingly, there is a long line of research documenting such links, be it from theoretical, empirical or policy directions.

Traditional finance theory associates high volatility with uncertainty about future investment payoffs and hence, uncertainty about the relevant macroeconomic variables, such as investment and consumption. For instance, Keynes (1936) argues that the amount of investment is a key factor in economic performance, where it is affected by risk. In this sense, high volatility would lead to lower levels of investment and deterioration of economic conditions. The more uncertainty the investor faces, the lower the expected present value of the income from an investment would be. The modern literature reaches similar conclusions. The real options literature emphasizes that if the volatility of future payoffs increases, the value of an option to invest increases, delaying investment (Dixit and Pindyck, 1994). In this view, high volatility may lead to adverse outcomes or crises, via what we call the *high volatility channel*.

Moreover, the financial authorities focus on the high volatility channel in both macro-prudential and micro-prudential regulations, using high volatility as an indication of a pending crisis. That motivates official intervention where banks are required to reduce their risk-taking or increase capital.

The link between low volatility and crises—what we name as the *low volatility channel*—is the main focus of this paper. It has been also emphasized in the theoretical literature, but largely ignored by the empirical literature and regulators. Hayek (1960) observes the presence of a risk cycle as separate from the business cycle, whereby low risk encourages risk-taking. Minsky's (1992) instability hypothesis suggests that economic agents interpret the presence of a low risk environment as an incentive to increase risk-taking, which in turn may lead to a crisis. That would create a channel for low volatility to endogenously increase the probability of market turmoil and an eventual crisis.

Brunnermeier and Sannikov (2014) identify what they term the "volatility paradox" where low risk can paradoxically increase the probability of a systemic event. Similarly, Danielsson et al. (2012) use a general equilibrium framework to analyze how perceptions of risk affect investors' risk-taking and the perception of volatility, where even small changes in volatility can lead to rapid price movements associated with crises and endogenously affect volatility. Bhattacharya et al. (2015) model Minsky's (1992) hypothesis formally with the possibility of endogenous default, where agents update their expectations during good times and increase their leverage.

In contrast to the theoretical analysis, it has proven harder to empirically examine the relationship between financial market volatility, the real economy, and crises, giving rise to Paul Samuelson's famous 1966 quip "Wall Street indexes predicted nine out of the last five recessions!" The empirical literature examining the financial volatility–crises relationship generally focuses on 20th century United States data and finds that recessions or financial crises are associated with high volatility (see, for instance, Schwert, 1989, 1990; Hamilton and Lin, 1996; Fornari and Mele, 2009; Corradi et al., 2013).

This paper is also part of the vast empirical literature that studies the determinants of a banking crisis. A prominent early example is Demirguc-Kunt and Detragianhe (1998), who consider the factors affecting the probability of banking crises for 65 countries for the period of 1980 to 1994. By constructing a data set of banking and currency crises spanning 120 years, Bordo et al. (2001) document that capital controls affect the probability of a crisis. More recently, several authors have made use of the Reinhart and Rogoff (2009) database, including Reinhart and Rogoff (2011), who focus on banking crises and relevant variables affecting their likelihood. More recent studies along similar lines are Gourinchas and Obstfeld (2012); Jorda et al. (2010); Schularick and Taylor (2012).

The main contribution of this paper is the identification of low (relative to trend) volatility, rather than the actual level, as a strong predictor of financial crises. Our empirical results provide support for the theoretical predictions by demonstrating the presence of high and low volatility channels and reinforce the existing literature on the determinants of crises. We also demonstrate that low volatility over a prolonged period leads to higher risk-taking, supporting Minsky's hypothesis. Finally, we contribute to the literature that examines the nature of financial crises with new panel data sets by constructing a cross-country volatility data set spanning over 200 years.

3 Modeling volatility

Our question of interest is whether volatility predicts crises, using historically long and comprehensive volatility observations. We are aware of no database on historical volatility, but fortunately, it is possible to construct such a database by using existing data on stock market returns. Still, the coverage of the stock market data are not quite as wide-ranging as for crises. A country might not have an organized stock market for some part of its history or historians may not have reconstructed stock market indices from primary sources. Fortunately, we are able to construct volatilities for 60 countries, some dating back to 1800, using monthly prices of stock market indices collected by `www.globalfinancialdata.com`.

In what follows, we demonstrate the volatility modeling process by showing data from the United States, while the Web appendix, `www.ModelsandRisk.org/volatility-and-crises`, contains similar analyses for every country in the sample.

3.1 Measuring volatility and regimes

Volatility is a latent variable and there is no clear-cut way to determine what is the best way to model volatility. Ideally, we would have used daily market returns to calculate volatility. However, daily observations on stock markets are scarce. While we can go to the early 20th century for the United States, daily data for most, if not all, of the other countries exist only 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.

In our particular case, the choice of a method is affected by the application: using monthly market returns to estimate volatility measures at the annual frequency. For daily returns, the GARCH model of Bollerslev (1986), and its direct descendants are often seen as the best volatility measure. However, when it comes to monthly returns like we have, GARCH may not be the best choice for three reasons. First, it requires a few hundred observations to be accurately estimated, and in our case that would mean several decades for in-sample estimations, not leaving enough observations for our analysis, and precluding out-of-sample predictions. Second, while the GARCH model captures well daily fluctuations, they tend to die out quickly and there are not nearly as strong GARCH effects in the data at the monthly frequency. Finally, GARCH is based on shocks to a mean reverting volatility process, and may therefore not be well suited to capture multi-decade volatility regimes, each with very different levels.

Instead, we opted to use the realized volatility and measure annual volatility by the standard deviation of 12 monthly returns.[3] It does not suffer from the drawbacks of the GARCH in our specific context.

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). For cases in which only quarterly, not monthly, CPI is available, we interpolated the quarterly CPI to the 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.

Not surprisingly, in such a comprehensive sample of stock market returns, a number of extreme observations occur, generally due to disruptive events like war and hyperinflationary periods. In such cases, the unconditional volatility is likely to be biased, as discussed by Muler and Yohai (2008), for whom it is preferable to use robust estimators of volatility by bounding extreme observations. Hence, similar to Han (2013) and Wahal

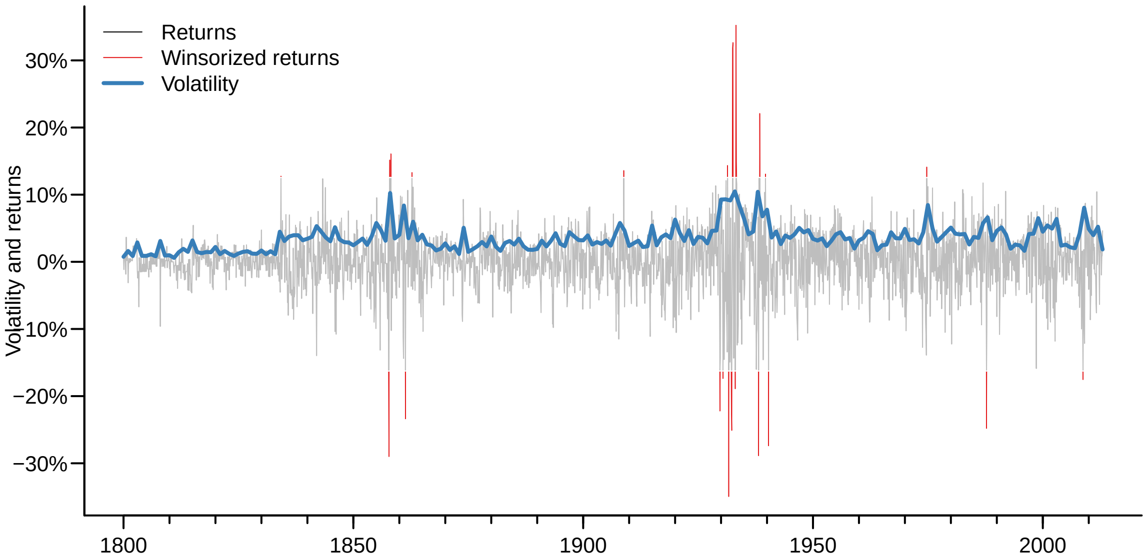
[3]We also estimate annual volatility as the sum of the absolute value of real returns, yielding qualitatively similar results as discussed in Section 5.6.

and Yavuz (2013), we winsorize 1% of monthly real returns for each country separately, prior to the estimation of volatility.[4]

Figure 1 shows the time-series plot of the monthly real returns, winsorization and the resulting annual volatility. The figure shows that episodes when winsorization is applied all correspond to wars or major crises, like the Civil War, the Great Depression, and the 1908, 1987, and 2008 crises.

Figure 1: **Return and volatility estimates for the United States**

Monthly real stock market returns (adjusted with CPI), winsorized real returns at the 1% level, and volatility estimates for the United States. Volatility is calculated as the standard deviation of 12 winsorized monthly real returns.



3.2 Descriptive analysis: volatility

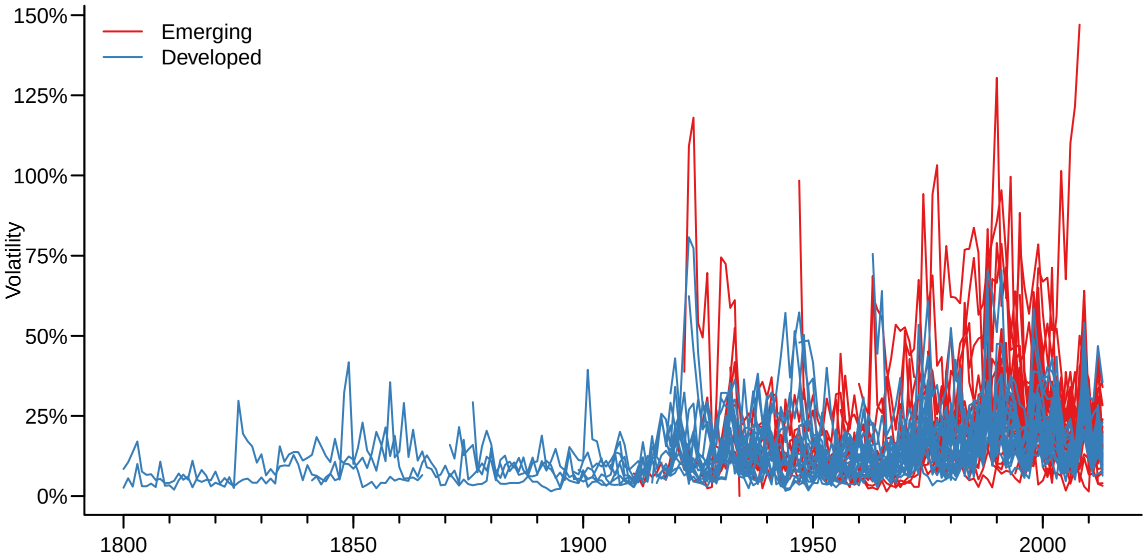
Figure 2 shows the volatility for each country in the sample, as their data become available. Only data for the United States and Great Britain are available from 1800, while data for France, Germany, and Australia from the mid-19th century. However, a large number of countries only developed stock markets after the World War I. The figure further shows that emerging countries have more volatile stock markets than developed

[4]More specifically, if a given country's real monthly return is above its 99.5th percentile, we set the return as the top 99.5th percentile value. Real returns below the 0.5th percentile are winsorized analogously. Results are robust to non-winsorization and winsorization at the 5% level.

countries. Indeed, we find that the annual stock market volatility of emerging countries averages 23%, compared with 16% for developed countries.

Figure 2: **Time-series plot of volatilities for developed and emerging countries**

The annual volatility level, calculated as the standard deviation of the previous 12 winsorized monthly real returns scaled by $\sqrt{12}$, for all of the countries in our sample, as their data become available. The estimates for the developed and emerging countries are labeled with different colors, where the classifications are adopted from the IMF definition. The sample spans 1800–2010 and includes 60 countries.

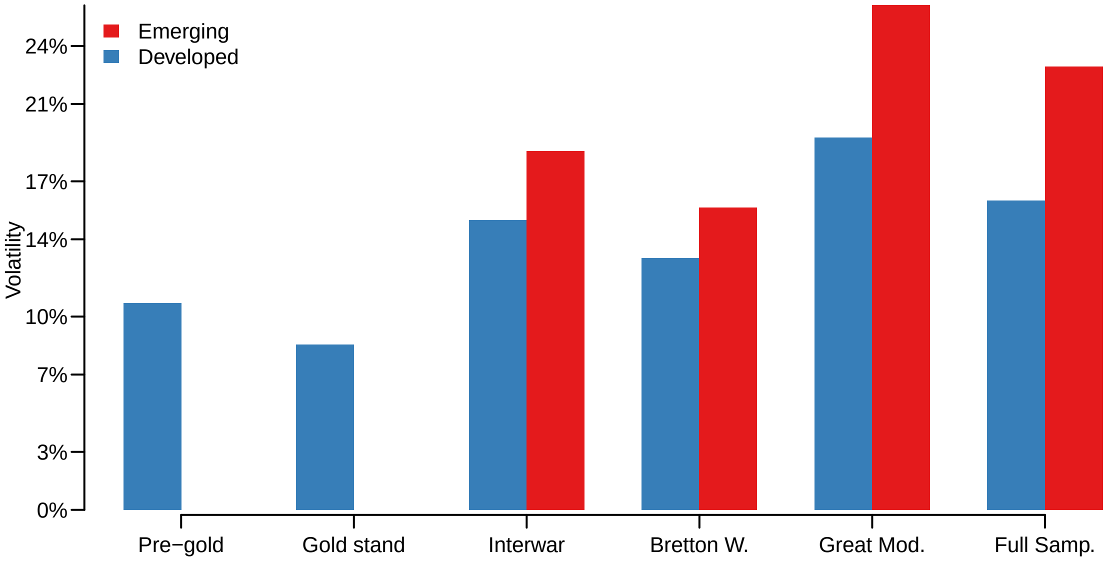


A similar picture emerges from Figure 3, which shows the average volatility for sub-periods of the data, segmented by emerging and developed countries. Although many interesting sub-periods within the sample merit special attention, to keep the discussion tractable, we opt to focus on five of the most interesting: the pre-gold period (1800–1872), the gold standard era (1873–1913), the interwar years (1919–1938), Bretton Woods (1949–1972), and finally the so-called Great Moderation (the two decades before the 2008 crisis).

Within the periods we consider, financial volatility is the highest during the 1985–2006 period, with the interwar years not far behind. This is interesting as the years of the Great Moderation tend to be associated with the lowest macroeconomic volatility, at least for developed countries (see e.g. Blanchard and Simon, 2001; Bernanke, 2012). One source of high volatility during the Great Moderation for emerging countries is the multiple crises suffered by some Asian and Latin American countries during that period.

Figure 3: **Volatility levels–sub-periods**

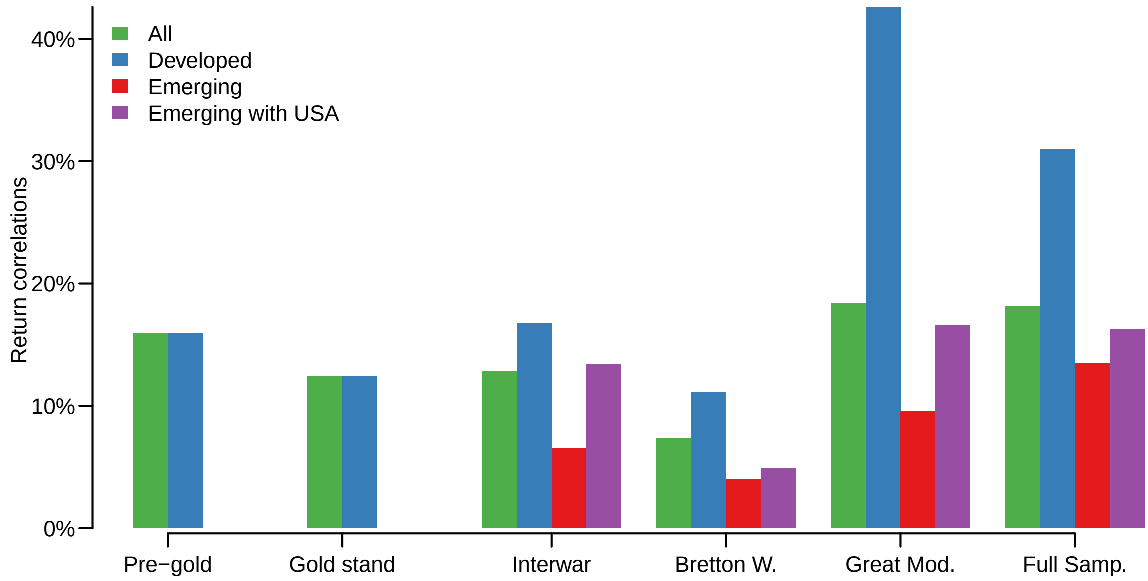
Average volatility levels for sub-periods for developed and emerging countries separately. The pre-gold (1800–1872), gold (1873–1913), interwar (1919–1938), Bretton Woods (1949–1972), and Great Moderation (1985–2006) periods as well as the whole sample period (1800–2010), are considered. Volatility is calculated as the standard deviation of the previous 12 winsorized monthly real returns, scaled by $\sqrt{12}$, and the sample includes 60 countries. Emerging and developed countries' classifications are adopted from the IMF definition.



These results are augmented by Figure 4, which shows the correlations between monthly real returns for developed and emerging countries. We see that within our 211 years of history, stock markets have always been quite related to each other. In the earliest period, we only have a handful of countries, and even though there was a limited electronic communication between countries or across the Atlantic, the stock market correlations still exceeded 15%. The correlations are lowest during the Bretton Woods era, when capital controls were in widespread use, limiting cross-border investment. If one uses correlations as a proxy for how financial markets are integrated with each other, these results suggest that market integration is in part driven by regulations. Since then, correlations have increased sharply. Indeed, the highest correlations are recorded during the last part of the sample (after 2007). Finally, although emerging countries have quite a low level of correlation between them, their returns are, as expected, highly correlated with those of the United States.

Figure 4: **Correlations**

The average monthly return correlations of all, developed and emerging countries, separately. The average correlation between the emerging countries' and the United States' returns are also presented. We first calculate the bilateral correlations between the countries with available data for a given period. We then report the cross-sectional averages. The pre-gold (1800–1872), gold (1873–1913), interwar (1919–1938), Bretton Woods (1949–1972), and Great Moderation (1985–2006) periods, as well as the whole sample period (1800–2010), are considered. The sample includes 60 countries. Emerging and developed countries' classifications are adopted from the IMF definition.



3.3 Decomposing volatility

We examine whether the high and low volatility channels are significant determinants of the incidence of a financial crisis. Hence, we need a methodology to identify these channels.

Figure 5 suggests the presence of a slow-moving, non-monotone trend spanning multiple decades, with two main peaks, corresponding to the Civil War and the Great Depression. The trend in the 1860s is around 20%, dropping to about 7% in the 1890s, increasing to 27% during the interwar period, and decreasing back to 8% in the 1960s. Similar patterns exist for other countries.

Furthermore, the level of volatility differs considerably across countries at any given time. These two combined effects—the presence of a slow-moving trend and heterogeneous volatility levels—have the potential to frustrate empirical analysis. The reason is that a particular measurement of volatility could be seen as high, low, or typical depending on the country or year.

We address this problem by decomposing volatility (σ) with the Hodrick and Prescott (1997) (HP) filter into trend (τ) and deviation from trend (δ), in different contexts referred to as cycle.

$$\sigma_t = \tau_t(\lambda) + \delta_t(\lambda), \quad t = 1, 2, ..., T, \tag{1}$$

where λ denotes the smoothing parameter, which quantifies the degree to which volatility is trend. The higher the λ, the smoother the trend and hence, the closer δ is to σ.

The standard two-sided HP filter uses the entire sample to construct the filter at time t. This means that information that is unavailable when macro-prudential policy decisions are actually made is used to construct the trend. As our analysis builds on predictive regressions, we need to construct explanatory variables using only past information. Therefore, we use the one-sided filter, i.e., we run the standard HP filter recursively through time by using only data available up to year t, estimate the trend and retain the final value as the trend for year t. This recursive setting assumes that only current and past states influence the current observation.

In order to identify the high and low volatility channels, we further separate the deviation of volatility from its trend into two components. We use the terms high volatility (δ^{high}) and low volatility (δ^{low}) to indicate these two cases.

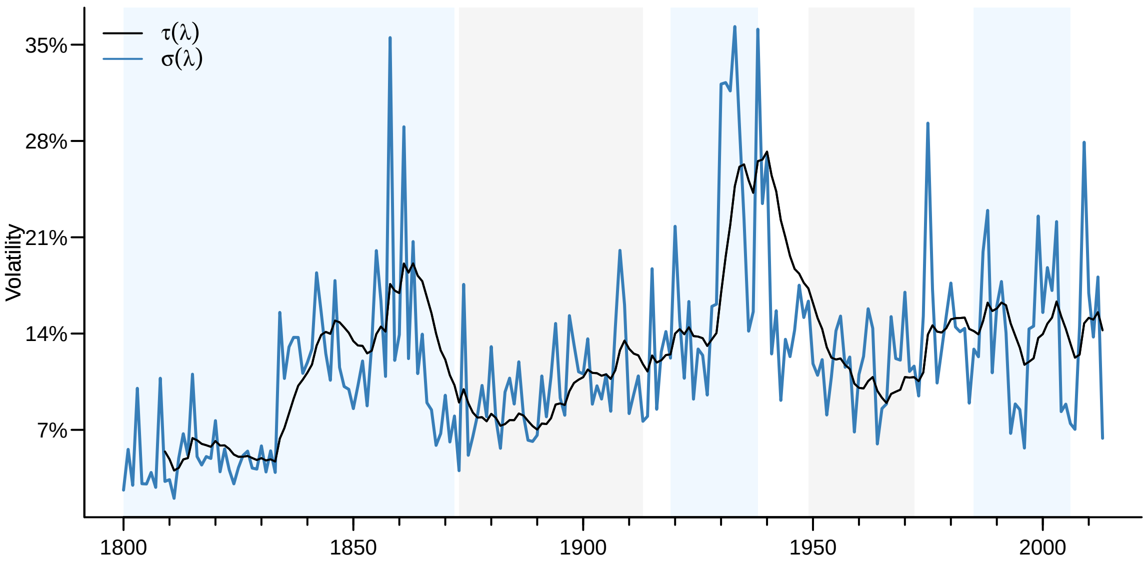
$$\begin{aligned} \delta_{\text{t}}^{\text{high}}(\lambda) &= \begin{cases} \sigma_t - \tau_t(\lambda) & \text{if} \quad \sigma_t \geq \tau_t(\lambda) \\ 0 & \text{otherwise,} \end{cases} \\ \delta_{\text{t}}^{\text{low}}(\lambda) &= \begin{cases} |\sigma_t - \tau_t(\lambda)| & \text{if} \quad \sigma_t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

Note that we use absolute value of low volatility in regressions to ease the interpretation of the estimated coefficients.[5]

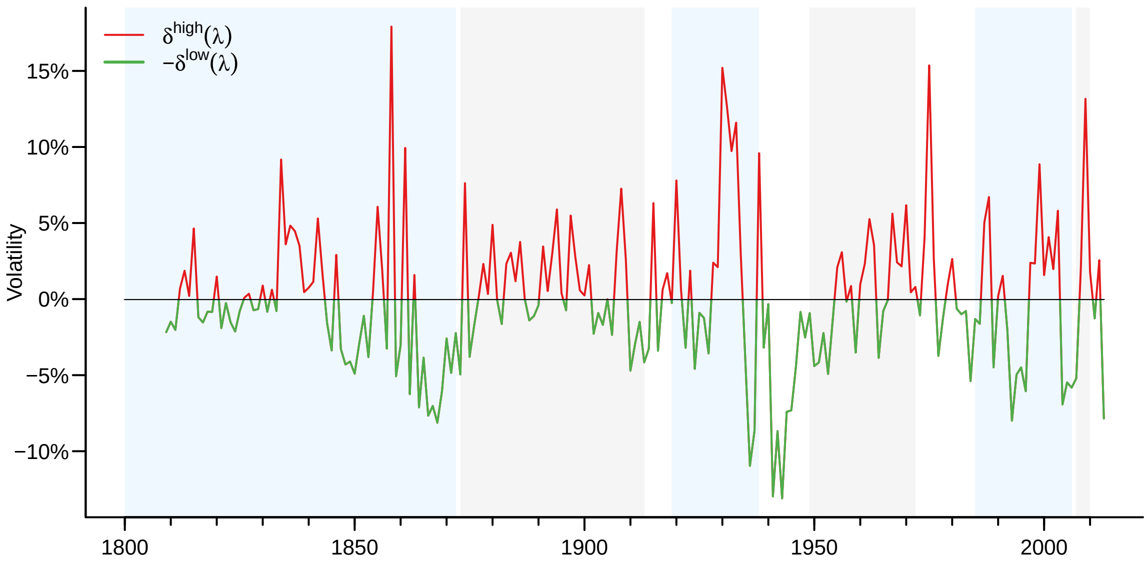
[5]The other alternative way to identify high and low volatility would be to use regime switching models, where the probability of jumping between high and low risk regimes is determined by a Markov process. However, Markov switching models of volatilities are not very precise when the sample size is not large. Moreover, it is empirically difficult to identify many states. That might leave us with the

Figure 5: **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 is applied to decompose volatility level into trend and deviations from the trend. In Panel (a), we mark the areas of volatility where it is both above and below 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 Great Moderation (1985–2006) periods are highlighted.



(a) Trend and volatility



(b) High and low volatility

Figure 5 visualizes the volatility, trend, and high and low components of volatility for $\lambda = 5000$. One can argue that the chosen smoothing parameter makes the trend quite flexible to be interpreted as a long-run level. However, increasing the persistence of the filter may remove long-run factors such as changes in the financial system or the regulatory system, whereas keeping a small parameter assigns a very large fraction of temporary changes to the trend. As discussed in the robustness section, our results are invariant to the chosen smoothing parameter; we reach qualitatively similar conclusions for λ =100, 1000, or 10000. Panel (a) shows the volatility level (σ) and estimated trend (τ), marking the areas in which volatility is higher and lower than the trend for the United States, while Panel (b) shows the high and low deviations from trend—i.e., δ^{high} and δ^{low}.

4 Econometric methodology

4.1 Model construction

We regress the binary crisis indicator $C_{i,t}$, which shows whether a banking crisis started in country i in year t, on lags of high and low volatility defined in Section 3, δ^{high} and δ^{low}. We also include control variables (X) and fixed effects.

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 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 run the following logit-panel regression:

$$\begin{aligned} C_{i,t} &= \beta_1 \overline{C}_{i,t-1 \text{ to } t-L} + \beta_2 \overline{\delta}^{\text{high}}_{i,t-1 \text{ to } t-L}(\lambda) + \beta_3 \overline{\delta}^{\text{low}}_{i,t-1 \text{ to } t-L}(\lambda) \\ &+ \beta_4 \overline{X}_{i,t-1 \text{ to } t-L} + \nu_t + \eta_i + \varepsilon_{i,t}, \quad i = 1, N \end{aligned} \tag{3}$$

simultaneous problem of not being able to do out-of-sample analysis and having an inaccurate volatility estimate with too few regimes. For this reason, we opted not to take the Markov switching approach.

where, the moving average variables are constructed as:

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

λ is the HP filter smoothing parameter, and ν_t and η_i are the time-series and cross-sectional fixed effects, respectively. When we use year and country fixed effects we face identification issues since crises are rare events and we use macroeconomic variables as controls. Thus, we opted to use less "granular" fixed effects at the decade and region level of aggregation. 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.

4.2 Financial crisis data

We base our analysis on the banking crises in Reinhart and Rogoff's (2009) database. A banking crisis is identified by (a) the closure, merger or public takeover of one or more financial institutions as a consequence of bank runs or (b) if there are no bank runs, the closure or large-scale government assistance of an important financial institution that leads to similar outcomes for other financial institutions.

The database includes 70 countries spanning the period from 1800 to 2010. However, the coverage of countries with sufficiently long volatility histories is somewhat smaller at 60. Hence, that becomes our final cross-section size. In total, we observe 262 banking crises, which combined with volatility data lead to a sample of 3700 country-year pairs.

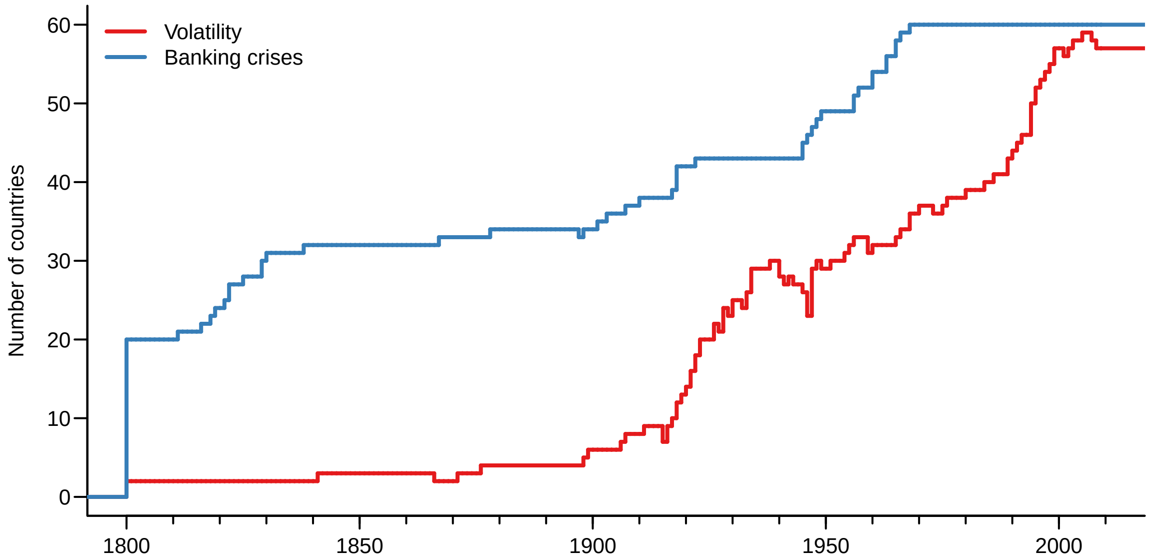
Figure 6 shows the data coverage. More crisis data are available than volatility data, especially at the beginning of the sample period. For example, volatility is available only for the United States, Great Britain, Germany, and France until the mid-1800s. In the 1920s the sample covers 10 countries, reaching 30 countries by the 1940s.

4.3 Control variables

Besides time-series and cross-sectional fixed effects, we control for specific circumstances that may provide alternative explanations with country specific control variables. In

Figure 6: **Data Coverage**

Number of countries with available volatility and crisis data.



particular, we consider lags of the crisis dummy, GDP per capita, inflation, change in government debt, and institution quality.

Following Demirguc-Kunt and Detragianhe (1998) and Cavallo and Frankel (2008), we use the natural logarithm of GDP per capita ($\ln GDP$), obtained from the Maddison economic database of Bolt and van Zanden (2014). Since we are considering the impact of real financial market volatility on crisis probabilities, it is also natural to control for the level of inflation, calculated as the annual percentage change in the consumer price index, obtained from Global Financial Data.

In addition, as government debt potentially affects the probability of a crisis, we also include $\Delta PD/GDP$, the change in gross central government debt-to-GDP ratio, in the regression specification. The data are obtained from Reinhart and Rogoff (2010).

Institutional characteristics and governance of a country can affect political and macroeconomic stability (Alesina et al., 1992; Acemoglu et al., 2003; Cerra and Saxena, 2008). Therefore, we use the POLCOMP variable from the Polity IV Project database as a proxy for "institutional quality". 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.

4.4 Econometric considerations

There are some considerations that have to be taken into account in the estimation. First, one needs to decide on the time period over which to calculate the annual volatility—January to December, July to June, or any other 12-month period. After all, all that is known is whether a crisis happened in a given year, not the month of the crisis. Even if the beginning month of crisis is marked, it is hard to verify the precise timing of a crisis as 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. We opted for mid-year volatility estimates, calculated by using returns from July to June of a given year and discuss other alternatives in the robustness analysis. Specifically, to estimate volatility for year t, we employ monthly return observations from July in year $t-1$ up to June in year t.

Second, one needs to decide the value of L in (3). Theory only suggests that past levels of volatility affect the future incidence of crises, but not how far back to look. The answer could easily depend on the time period or the country under consideration (see for instance Aguiar and Gopinath, 2007, who show that the business cycles of emerging countries are shorter than the developed ones). In what follows, we opted for five years, but in Section 5.1 we examine different lag lengths.

Finally, since we estimate high and low volatility with HP filtering we need to specify the smoothing parameter λ. The choice of λ depends on the nature of the underlying time-series. For instance, for annual GDP data from the United States, Hodrick and Prescott (1997) propose a λ equal to 100. Given that our series is stock market volatility and it is more volatile compared to a macroeconomic series, like GDP, we chose a larger smoothing parameter. Otherwise, the procedure would assign a very large fraction of swings to the trend, making it almost the same as volatility itself. In the baseline specifications, we set λ =5000; however, we investigate other alternatives in the robustness analysis.

5 Results

Our regression analysis shows the impact of volatility on the probability of future crises within a panel-logit regression framework. We focus on three different specifications of volatility: the annual level of volatility (σ), volatility above its trend (δ^{high}), and volatility below its trend (δ^{low}). In what follows, we refer to these as level, high, and low volatilities, respectively.

5.1 Volatility and crises

The first relationship we consider is how the volatility level relates to the probability of future crises, presented in Table 1, Columns I and II. When considered on its own as an independent variable, σ 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.

The theoretical literature suggests that both high and low volatility may affect agents' decision making, leading to a deterioration of financial conditions. If the impact of these two effects is different, it is possible that the level of volatility is insignificant while high or low volatility is significant. This motivates the separation of high and low volatility channels, which is confirmed by the results in Table 1.

The coefficient of both high and low volatility is positive and significant in the absence of control variables (Column III, Table 1). Since we use the absolute value of low volatility, the higher the δ^{high} and δ^{low} are, the farther away volatility is from its trend in either direction and the higher the likelihood of a crisis. We observe that the economic impact of low volatility is higher than that of its high volatility counterpart. A 1% decrease in volatility below its trend translates into a 1.12% increase in the probability of a banking crisis, whereas the economic impact of high volatility is 0.96%. Moreover, only δ^{low} survives the inclusion of control variables. The strong prediction of δ^{low} is in line with theoretical results where low volatility induces excessive risk-taking, leading to future credit problems and difficulties for banks. High volatility is not significant in the presence of control variables, indicating that the low volatility channel matters lending support to Chair Yellen's observation at the start of the paper.

The observation that the level of volatility is not a significant predictor of crises when controlled for macroeconomic variables leaves the question of the extent to which the control variables predict volatility. We find that about half of the variation in volatility can be explained (adj. R^2) by macroeconomic variables, where it is only 11% and 16% for high and low volatility, respectively. Therefore, if one wants to capture the impact of deviations of risk from what economic agents expect it to be, it is necessary to look at the high and low decomposition; otherwise, one might as well just look at the macroeconomic dynamics.

Our findings presented so far rely in backward moving averages of explanatory variables using the previous five years. In Table 2, we examine the predictive power of low volatility by using different lag lengths. The results indicate a positive and economically significant relationship between low volatility and future financial crises when information up to 11 years is taken into account to calculate the historical average of low volatility. Marginal effects reveal that the economic importance increases monotonically and reaches a maximum when five years of backward moving average is used.

In addition to volatility gap, we find that 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.

Interestingly, we find that the increase in the debt-to-GDP ratio is negatively associated with the probability of a future banking crisis. This is in line 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.

5.2 Low volatility and risk-taking

The results presented indicate the presence of low volatility channel, which can be motivated by low risk environment encouraging economic agents to engage in excess risk-taking that ultimately triggers a crisis—what is often termed the "Minsky hypothesis". In this section, we further explore whether long-lasting low volatility periods leads to higher risk-taking.

We could not use the whole sample because no variable capturing risk-taking exists until later in the sample and the earliest risk-taking proxies do not cover the whole cross-section. Even in more recent history, measuring risk-taking is not straightforward. One could use bank-level data, such as bank capital-to-asset ratio or non-performing loans ratio, but such data are quite restrictive, and it is difficult, if not impossible, to aggregate it at the country level.

Our risk-taking proxy adopts the Basel Committee on Banking Supervision's credit-to-GDP ratio gap, which is identified and used as a signaling device for the build-up of excessive leverage for banks (Alessi and Detken, 2014). Indeed, Drehmann et al. (2010, 2011) show that it outperforms other early warning indicators such as GDP, credit growth, and their ratios, as well as other banking sector performance measures.

Credit-to-GDP ratio gap is defined as the difference between the actual credit-to-GDP ratio and the long-run trend, where 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. We opt for its median value of $\lambda = 100$, but did consider others without any significant changes to the results.[6] We obtain aggregate private sector credit data, as a percentage of GDP from the BIS. The downside is that these data are only available from the 1960s for 35 countries.

To examine whether low volatility for a prolonged period of time leads to an increase in risk-taking behavior, we regress risk-taking on high and low volatility:

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

[6] For quarterly data, $\lambda = 1600$, 25000, 125000, and 400000, are equivalent to $\lambda = 6$, 100, 500, 1500 in annual data (Ravn and Uhlig, 2002). This assumes that the credit cycle is the same, double, triple, and quadruple as the length of the business cycle of $7\frac{1}{2}$ years.

We include all of the control variables introduced in (3). In addition, we control for the level of interest rates as it is expected to be an important determinant of credit growth.

The results reported in Table 3 show that the estimated coefficient of low volatility is positive and significant for various lag-lengths used to obtain backward-looking moving averages (L). Hence, we find strong support that low levels of financial volatility are followed by credit booms, supporting the Minsky's instability hypothesis. We see that the past five years' volatility has the highest economic impact on credit growth, whereas the effect diminishes after five years and dies out for $L = 13$. This finding is intuitive: to alter agents' expectations and allow for imbalances to build-up, volatility should be persistently low, for at least couple of years. After long periods though, "unusually" low volatility becomes "usual" and agents are not likely to continue taking excessive risk during normal conditions.

We conduct various robustness checks to confirm our findings. One can argue that the credit-to-GDP gap may not be the best variable to use because it tends to adjust slowly following a long period of negative credit growth. In addition, a higher gap could be due to either excessive credit growth or low output growth, meriting different policy responses (see, for instance Edge and Meisenzahl, 2011; Alessi and Detken, 2014; Bassett et al., 2015). We therefore use the growth of the credit-to-GDP ratio as a proxy for risk-taking.

We also make use of 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 our conjecture by using a fairly long historical data but covering only a few countries, in addition to the BIS data, which is cross-sectionally 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 non-financial corporations (excluding lending within the financial system).

We then investigate whether our results are sensitive to other model specifications. In particular, we remove the lagged dependent variable, we remove all of the control variables, and we include the credit trend (τ) estimated through the HP filter in the baseline specification.

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. However, there is no obvious reason to believe that June to July would be better than any other 12-month period. Thus, we first test the results when volatility is calculated by employing monthly returns up to March, September, and December. For the sake of brevity, we present the end-year results only. In addition, following Mele (2007); Fornari and Mele (2009); Corradi et al. (2013), we measure volatility as the sum of absolute monthly returns, instead of standard deviation.

Fifth, we examine the sensitivity of the results to the smoothing parameter λ in the HP procedure. We consider λ =6, 500, and 1500 but as the results are qualitatively similar, we report the results only with λ =6.

Finally, we examine whether our findings are driven by the 2008 global financial crises.

The results reported in Table 4 indicate that our finding is robust; the relationship between low volatility and future credit booms is qualitatively similar and highly significant under different robustness tests we undertake.

5.3 Reliability of low volatility as a financial crisis predictor

While our results reveal that current deviations of volatility from its long-run level indicate that a financial crisis is more likely a few years down the road, they do not by themselves suggest that high and low volatility would be valuable early warning indicators. Assessing their reliability is of key interest for policymakers, and for that reason we examine such a predictability along two dimensions. First, we formally evaluate the degree of type I and type II errors—the tradeoff between missing actual distress episodes and creating false alarms. Second, as in-sample regressions give rise to the potential for the forecast results being affected by look-ahead bias, we examine the out-of-sample forecasting performance of high and low volatility.

One standard way to evaluate binary classification ability is to calculate the area under the receiver operating characteristic curve (AUROC), which is a test of whether the signals are distributed significantly different under crisis and non-crisis periods. The AUROC provides a measurement of the accuracy of a signal by considering the true positive rate (signal ratio) against the false positive rate (noise ratio) for every possible threshold value. As the threshold increases, the number of crisis signals drops, so fewer crises are correctly identified and incorrectly signaled, while under a lower threshold more crises are correctly identified while the frequency of false signals also increases. A key advantage of the AUROC approach is that it does not rely on a specific threshold; consequently it has been widely used as an evaluation criterion in recent literature, including Berge and Jorda (2011); Candelon et al. (2012), and Schularick and Taylor (2012).

If a signal is non-informative, equivalent to the toss of a coin, the AUROC would be 50%. In our case, we find that for banking crises the AUROC is 77%, with a 95% confidence interval of $[73\%, 80\%]$. This clearly indicates that unusual volatility signals a crisis significantly better than random noise. While there is no established cut-off value in the literature to classify an indicator as strong, Schularick and Taylor (2012) find an AUROC of 72% for the predictive ability of credit booms on a banking crisis.

To evaluate the out-of-sample performance, we split the panel into two subsample periods: the training period (T_{train}) and the testing period (T_{test}) with $T_{\text{train}} + T_{\text{test}} = T$, the total number of years. Then, for a subsample of observations up to $t = T_{\text{train}}$, we estimate the logit-panel regression model from (3) by including only high and low volatility and fixed effects. Having the estimated coefficients, we compute the predictive value of the model at $t+1$ ($\widehat{C}_{t+1}$) for each country. We repeat this procedure from T_{train} up to $T-1$ by adding one year of observation each iteration. We then calculate the pseudo-R^2 of Estrella (1998); Estrella and Mishkin (1998), defined for each country as

$$\text{pseudo-}R^2 = 1 - \left(\frac{\log Lu}{\log Lc}\right)^{-\frac{2}{T_{\text{test}}}\log Lc}, \tag{6}$$

where Lu and Lc are the log-likelihood of the unrestricted model and a model that only includes fixed effects. The log-likelihood is obtained as:

$$\log L = \sum_{T_{\text{train}}+1}^{T} C_t \log(\widehat{C}_t) + (1 - C_t)\log(1 - \widehat{C}_t) \tag{7}$$

where C_t and $\hat{C}_t$ are the realized and the predicted probability of recession for years t.

Finally, we get the cross-sectional averages of pseudo-R^2s. If the inclusion of high and low volatility, in addition to fixed effects, delivers a better out-of-sample performance than fixed-effects only, then we should observe positive pseudo-R^2s.

We calculate the pseudo-R^2 for a range of T_{train} finding positive values in all cases. For example, setting T_{train} to 1960 and 1980, the pseudo-R^2 is 18.0% and 21.4%, respectively.

Although we acknowledge the early warning literature's healthy skepticism of the quality of an indicator, our results suggest that relatively high and low volatility provide a statistically significant indication of future crises both in-sample and out-of-sample, delivering a fair signal-to-noise ratio. Therefore, we believe that they could be seriously considered by policymakers as a guidance on the volatility–crises relationship.

5.4 Volatility and crises: sub-periods

Throughout the sample period, we witness many different economic and market structures. In the beginning of the sample, we have very few countries and no electronic communication, while in 2010 we have advanced integrated financial and economic systems. Moreover, the structure of the banking system, stock market developments, and capital restrictions have changed dramatically.

In addition, several different currency systems were in operation; the gold standard with the occasional realignment pre-World War I, some countries temporarily returning to the gold standard in the interwar years, followed by the fixed exchange rate regimes of the Bretton Woods era, and a variety of arrangements since then. Not surprisingly, the frequency of crises has been changing as well. The pre-World War I era has the lowest frequency of crises, while the interwar and Great Moderation periods are more crisis prone.

In the specific context of volatility, stock markets have become steadily more important over time. In the earliest part of the sample, limited liability corporations were quite uncommon. Almost all banks were partnerships and hence had different incentives of risk-taking than recent banks, which are mostly limited liability corporations. 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). Stock markets first start to play a major economic role in the interwar years, and then primarily in the United States.

In addition, volatility level changed dramatically following these developments throughout the sample period, as documented in Section 3.2. Ultimately these suggest to us that it is worthwhile to study the volatility–crises relationship in different sub-periods.

We examine three important sub-periods. First, we merge the pre-gold and gold standard eras under the early period (1800–1913), as the sample is otherwise too small for a proper statistical analysis. We also consider the post-war II era from 1946 to 2010. Finally, we examine the period of great moderation (1985–2006). The results are presented in Table 5.

In the early period, we find that neither high nor low volatility is significantly related to banking crises. The postwar era is the first time stock markets and banking, especially in the United States, became available to most economic agents and we had many more limited liability corporations than before. Consequently, we find that low volatility increases the probability of banking crises. Finally, there is a natural breaking point in the mid-1980s marking the start of the Great Moderation, when inflation was conquered and computers were used for financial trading. This is the period when markets were highly integrated due to technological improvements and the opening of capital flows. Similar to the whole sample, we find that during the Great Moderation, only the low volatility channel matters.

5.5 Other crises

In this section, we examine the predictive power of high and low volatility over other varieties of financial crises: stock market and currency crises. To this end, we employ the historical crisis records of Reinhart and Rogoff (2009), where they identify 419 stock market crises and 540 currency crises. A currency crisis indicates a currency reform, such as an abandonment of a pegged exchange rate or a 15% or more depreciation of a currency with respect to the U.S. dollar (or the sterling, French franc, German mark or euro), whereas a stock market crisis is marked in case of a cumulative decline of 25% or more in real equity prices (Barro and Ursua, 2009).

Table 6 presents the results. For stock market crises, both the δ^{high} and δ^{low} coefficients are positive and significant. High volatility could reflect the increased uncertainty about future economic conditions, where a negative eventuality would cause prices and stock markets to sharply fall. At the same time, long periods of low volatility may also induce excessive risk-taking in a Minsky-type scenario, also indicating a higher chance of a future stock market crisis. Furthermore, since the probability of a stock market crisis derives from the same stochastic process as volatility, it may well be that more extreme high or low volatilities could indicate that the tails of the return process are becoming fatter, increasing the probability of a crisis.

We further investigate the impact of volatility on stock market crises employing different lag lengths. The results reported in Table 7 indicate that the low channel is most important farther away from a crisis while the high channel operates much closer to a crisis. In particular, when the information up to the previous three years is used to calculate the historical averages for volatility, we find that only high volatility matters for predicting stock market crises, whereas low volatility becomes important only when agents observe low levels of volatility for a "long-enough" period, such as five years. Accordingly, when we consider volatility during the last seven years, low volatility becomes the only significant predictor of a stock market crisis. Indeed, we find that low volatility Granger causes high volatility, but not vice versa. These results are consistent with what one would expect from the economic theory—the low volatility channel induces risk-taking and as we move through time, volatility increases at the onset of a stock market crisis. Hence, there is a sequence; a few years later following low volatility, high volatility signals a crisis is around the corner.

By contrast, volatility has no impact on currency crises regardless of whether the control variables are included. This is not entirely unexpected; among the three financial crisis types considered in this study, currency is the most closely connected to the macroeconomy and the connection to financial market volatility is the most tenuous.

5.6 Robustness

The volatility–crisis link, as presented so far, is based on a plausible set of model and parameter assumptions. As usual, there is more than one way to make many of these assumptions, and in this section we consider several alternative cases to test robustness.

We first examine different ways of capturing the high and low volatility channels. Perhaps the most obvious alternative is the deviation from a mean rather than deviation from 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. Inspired Loayza et al. (2007), we calculate volatility that corresponds to large positive and negative fluctuations outside a one-standard deviation band.

Second, we check whether our findings are sensitive to the definition of volatility. We first test the results when volatility is calculated as the standard deviation of 12 monthly end-year (January to December), rather than mid-year returns. In addition, we measure volatility as the sum of absolute monthly returns, instead of standard deviation.

Third, we include the level of real interest rates and the credit-to-GDP ratio gap in order to control for economic conditions.[7]

Fourth, we examine whether the empirical methodology and model specification matters. We re-run regressions without any time and cross-sectional fixed effects and include the results 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.

Fifth, 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.

Finally, we investigate whether our main results are still present if we use different samples. In particular, we exclude volatile periods such as the interwar period, the two world wars, and the post-2007. We then test the sensitivity of our findings by employing 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 appraised in the literature (Jalil, 2015; Romer and Romer, 2015). Hence, we merged the databases of Bordo et al. (2001); Laeven and Valencia (2008); Gourinchas and Obstfeld

[7]Data on interest rates and credit is taken from the BIS for 35 countries from 1960s. As our study takes an historical perspective, we left the inclusion of these variables as a robustness check.

(2012); Schularick and Taylor (2012) with that of Reinhart and Rogoff (2009) for banking by using consistent definitions of crises.[8]

Overall, Table 8 reveals 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 and the control variables hold up.

6 Conclusion

In this paper, we create an extensive dataset of financial market volatility from primary sources, spanning 60 countries and up to 211 years. This 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 asymmetry of the impact of high and low volatility on agents' decisions.

While the common view is that volatility directly affects the probability of a crisis, this has proven difficult to verify empirically. In what we believe is the first study to do so, we find direct empirical evidence that the level of volatility is not a good indicator of a crisis, but that relatively high or low volatility is. Low volatility increases the probability a banking crisis, both high and low volatility matter for stock market crises, whereas volatility–in any form–does not seem to explain currency crises.

We further use the credit-to-GDP gap as a proxy for risk-taking, and find that low volatility significantly increases risk-taking. This is very much in line with what theory predicts and provides strong evidence for Minsky's instability hypothesis and his famous

[8]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.

statement that “stability is destabilizing”. Low volatility induces risk-taking, which leads to riskier investments. When those turn sour, a crisis follows.

Finally, we find that the relationship between volatility gap and the incidence of a crisis becomes stronger over time, consistent with the observation that stock markets have grown in importance over the 211 year sample.

Our findings should be of value to macro-prudential and monetary policy policymakers, as they provide guidance on how one should think about the relationship between financial market risk and the macroeconomy.

References

Acemoglu, D., S. Johnson, J. Robinson, and Y. Thaicharoen (2003). Institutional causes, macroeconomic symptoms: Volatility, crises and growth. *Journal of Monetary Economics 20*, 49–123.

Aguiar, M. and G. Gopinath (2007). Emerging market business cycles: The cycle is the trend. *Journal of Political Economy 115*, 69–102.

Alesina, A., S. Ozler, N. Roubini, and P. Swagel (1992). Political instability and economic growth. *Journal of Economic Growth 1*, 189–211.

Alessi, L. and C. Detken (2014, August). Identifying excessive credit growth and leverage. ECB Working Paper Series 1546.

Barro, R., J. and F. Ursua, J. (2009). Stock market crashes and depressions. Technical Report 14760, NBER Working Paper.

Basel Committee on Banking Supervision (2010). Countercyclical capital buffer proposal. Technical report, Bank for International Settlements.

Bassett, W., A. Daigle, R. Edge, and G. Kara (2015). Credit-to-gdp trends and gaps by lender- and credit-type. FEDS Notes.

Berge, T., J. and O. Jorda (2011). Evaluating the classification of economic activity into recessions and expansions. *American Economic Journal: Macroeconomics 3*, 246–277.

Bernanke, B. (2012). *The Great Moderation*, pp. 145–162. Hoover Institution Press.

Bhattacharya, S., C. Goodhart, D. Tsomocos, and A. Vardoulakis (2015). A reconsideration of Minsky's financial instability hypothesis. *Journal Money Credit and Banking Forthcoming*.

Blanchard, O. and J. Simon (2001). The long and large decline in U.S. output volatility. *Brookings Papers on Economic Activity 1*, 135–174.

Bollerslev, T. (1986). Generalised autoregressive conditional heteroskedasticity. *Journal of Econometrics 51*, 307–327.

Bolt, J. and J. L. van Zanden (2014). The Maddison Project: Collaborative research on historical national accounts. *The Economic History Review 67*, 627–651.

Bordo, M., B. Eichengreen, D. Klingebiel, S. M. Martinez-Peria, and A. K. Rose (2001). Is the crisis problem growing more severe? *Economic Policy 24*, 51–82.

Brunnermeier, M. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economic Review 104*, 379–421.

Candelon, B., E. Dumitrescu, and C. Hurlin (2012). How to evaluate an early-warning system: Toward a unified statistical framework for assessing financial crises forecasting methods. Technical Report 60, IMF Economic Review.

Cavallo, E., A. and A. Frankel, J. (2008). Does openness to trade make countries more vulnerable to sudden stops, or less? Using gravity to establish causality. *Journal of International Money and Finance 27*, 1430–1452.

Cerra, V. and S. C. Saxena (2008). Growth dynamics: The myth of economic recovery. *American Economic Review 98*, 439–457.

Corradi, V., W. Distaso, and A. Mele (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics 60*, 203–220.

Danielsson, J., H. S. Shin, and J.-P. Zigrand (2012). Procyclical leverage and endogenous risk. Mimeo, LSE, `http://www.riskresearch.org`.

Demirguc-Kunt, A. and E. Detragianhe (1998, March). The determinants of banking crises in developing and developed countries. IMF Working Paper.

Dixit, A. K. and R. S. Pindyck (1994). *Investment under Uncertainty.* Princeton University Press.

Drehmann, M., C.Borio, L. Gambacorta, G. Jimenez, and C. Trucharte (2010, July). Countercyclical capital buffers: Exploring options. BIS Working Paper.

Drehmann, M., C.Borio, and K. Tsatsaronis (2011, November). Anchoring countercyclical capital buffers: The role of credit aggregates. BIS Working Paper.

Edge, R. and R. Meisenzahl (2011). The unreliability of credit-to-GDP ratio gaps in real time: Implications for countercyclical capital buffers. *International Journal of Central Banking 7*, 261–298.

Elliot, G. (2006). *Overend & Gurney, A Financial Scandal In Victorian London.* Methuen Publishing Ltd.

Estrella, A. (1998). A new measure of fit for equations with dichotomous dependent variables. *Journal of Business & Economic Statistics 16*, 198–205.

Estrella, A. and F. Mishkin (1998). Predicting U.S. recessions: Financial variables as leading indicators. *The Review of Economics and Statistics 80*, 45–61.

Fornari, F. and A. Mele (2009). Financial volatility and economic activity. Financial Markets Group Discussion Paper No. 642.

Gourinchas, P.-O. and M. Obstfeld (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics 8*, S85–S118.

Hamilton, J., D. and G. Lin (1996). Stock market volatility and business cycle. *Journal of Applied Econometrics 11*, 573–593.

Han, L. (2013). Understanding the puzzling risk-return relationship for housing. *Review of Financial Studies 26*, 877–928.

Hayek, F. (1960). *The Constitution of Liberty.* Routledge.

Hodrick, R., J. and C. Prescott, E. (1997). Postwar US business cycles: an empirical investigation. *Journal Money Credit and Banking 29*, 1–16.

Jalil, A. J. (2015). A new history of banking panics in the united states, 1825-1929: Construction and implications. *American Economic Journal: Macroeconomics 7*, 295–330.

Jorda, O., M. Schularick, and A. M. Taylor (2010). Financial crises, credit booms, and external imbalances: 140 years of lessons. Technical Report 16567, NBER Working Paper.

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

Laeven, L. and F. Valencia (2008). Systemic banking crises: A new database. Technical report, IMF Working paper WP/08/224.

Loayza, N., R. Ranciere, L. Serven, and J. Ventura (2007). Macroeconomic volatility and welfare in developing countries: An introduction. *The World Bank Economic Review 21*, 343–357.

Mele, A. (2007). Asymmetric stock market volatility and the cyclical behavior of expected returns. *Journal of Financial Economics 86*, 446–478.

Minsky, H. (1992). The financial instability hypothesis. Working Paper 74, Jerome Levy Economics Institute, Annandale on Hudson, NY.

Muler, N. and V. Yohai (2008). Robust estimates for GARCH models. *Journal of Statistical Planning and Inference 138*, 2918–2940.

Ravn, M., O. and H. Uhlig (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics 84*, 371–376.

Reinhart, C. M. and K. S. Rogoff (2009). *This Time is Different: Eight Centuries of Financial Folly.* Princeton University Press.

Reinhart, C. M. and K. S. Rogoff (2010). Growth in a time of debt. *American Economic Review: Papers & Proceedings 100*, 573–578.

Reinhart, C. M. and K. S. Rogoff (2011). From financial crash to debt crisis. *American Economic Review 101*, 1676–1706.

Romer, C. D. and D. H. Romer (2015, March). New evidence on the impact of financial crises in advanced countries. NBER Working Paper No 21021.

Samuelson, P. (1966). Science and stocks. *Newsweek*.

Schularick, M. and A. Taylor (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review 102*, 1029–1061.

Schwert, G. W. (1989). Business cycles, financial crises, and stock volatility. *Carnegie-Rochester Conference Series on Public Policy 31*, 83–125.

Schwert, G. W. (1990). Stock volatility and crash of 1987. *Review of Financial Studies 3*, 77–102.

Wahal, S. and M. Yavuz, D. (2013). Style investing, comovement and return predictability. *Journal of Financial Economics 107*, 136–154.

Yellen, J. (2014). Press Conference, Federal Reserve Board. June, 18.

Table 1: **Volatility channels 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, $\log GDP$ 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.

Dep. Var.: $C_{i,t}^{\text{Banking}}$	I	II	III	IV
$\sigma_{i,t-1 \text{ to } t-5}$	0.07**	-0.01		
	(0.027)	(0.049)		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$			0.26**	0.20
			(0.108)	(0.128)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$			0.30***	0.31***
			(0.097)	(0.115)
$C_{i,t-1 \text{ to } t-5}$	-6.71***	-7.46***	-7.32***	-7.86***
	(1.510)	(1.512)	(1.975)	(2.039)
$\log GDP_{i,t-1 \text{ to } t-5}$		-0.04		0.07
		(0.198)		(0.229)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$		-0.05**		-0.07***
		(0.022)		(0.026)
$POLCOMP_{i,t-1 \text{ to } t-5}$		-0.07		-0.09*
		(0.046)		(0.048)
$INFLATION_{i,t-1 \text{ to } t-5}$		0.03***		0.02
		(0.011)		(0.011)
Num of Obs.	3,054	2,850	2,219	2,134
Pseudo R^2	0.0988	0.122	0.0830	0.106
Marginal effects (%)				
$\sigma_{i,t-1 \text{ to } t-5}$	0.196	-0.037		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$			0.956	0.659
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$			1.118	1.011

Table 2: **Volatility channels and financial crises: different lag lengths**
This table presents the results for the regression equation introduced in (3) for $L = 1, 2, ..., 13$. 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 1. 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.

Dep. Var.: $C_{i,t}^{\text{Banking}}$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$	.	$L=10$	$L=11$	$L=12$	$L=13$
$\delta_{i,t-1 \text{ to } t-L}^{\text{high}}$	-0.01	0.03	0.12	0.14	0.20	.	0.17	0.12	0.10	0.06
	(0.083)	(0.116)	(0.112)	(0.132)	(0.128)	.	(0.176)	(0.192)	(0.184)	(0.195)
$\delta_{i,t-1 \text{ to } t-L}^{\text{low}}$	0.16**	0.19**	0.23**	0.27***	0.31***	.	0.24*	0.22	0.19	0.21
	(0.064)	(0.079)	(0.104)	(0.104)	(0.115)	.	(0.141)	(0.137)	(0.132)	(0.131)
$C_{i,t-1 \text{ to } t-L}$		-3.89***	-5.30***	-6.97***	-7.86***	.	-10.19***	-10.90***	-11.47***	-13.22***
		(1.148)	(1.558)	(1.571)	(2.039)	.	(1.837)	(1.956)	(2.473)	(2.554)
$\log GDP_{i,t-1 \text{ to } t-L}$	0.09	0.05	0.07	0.07	0.07	.	-0.02	-0.04	-0.07	-0.09
	(0.147)	(0.165)	(0.194)	(0.219)	(0.229)	.	(0.249)	(0.252)	(0.252)	(0.267)
$\Delta PD/GDP_{i,t-1 \text{ to } t-L}$	-0.01	-0.02	-0.04**	-0.05	-0.07***	.	-0.10*	-0.13**	-0.13***	-0.16***
	(0.010)	(0.016)	(0.021)	(0.034)	(0.026)	.	(0.055)	(0.051)	(0.050)	(0.046)
$POLCOMP_{i,t-1 \text{ to } t-L}$	-0.09**	-0.08**	-0.09**	-0.09**	-0.09*	.	-0.08*	-0.08**	-0.07*	-0.07*
	(0.040)	(0.041)	(0.043)	(0.043)	(0.048)	.	(0.044)	(0.039)	(0.040)	(0.038)
$INFLATION_{i,t-1 \text{ to } t-L}$	0.01	0.01	0.01	0.02	0.02	.	0.02	0.02*	0.02**	0.03**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.011)	.	(0.012)	(0.011)	(0.010)	(0.011)
Num of Obs.	1,946	2,085	2,108	2,124	2,134	.	2,175	2,183	2,191	2,199
Pseudo R^2	0.0656	0.0834	0.0916	0.0997	0.106	.	0.0880	0.0899	0.0908	0.0983
Marginal effects (%)										
$\delta_{i,t-1 \text{ to } t-L}^{\text{high}}$	-0.042	0.097	0.407	0.475	0.659	.	0.579	0.432	0.346	0.202
$\delta_{i,t-1 \text{ to } t-L}^{\text{low}}$	0.644	0.677	0.801	0.923	1.011	.	0.839	0.750	0.687	0.729

Table 3: **Low volatility and risk-taking**

The table presents the results for the regression equation introduced in (5) for $L = 1, 2, ..., 13$. The dependent variable, credit-to-GDP ratio gap ($CR\_GAP_{i,t}$), is the difference between the credit-to-GDP ratio and its trend, estimated by an HP filter with a smoothing parameter of 100. δ^{high} and δ^{low} are high and low volatility introduced in (2). $INTRATE$ is the real interest rate. The rest of the variables are introduced in Table 1. Credit-to-GDP data is obtained from BIS. The panel covers 35 countries and spans 1960–2010. 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.

Dep. Var: $CR\_GAP_{i,t}$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$	.	$L = 10$	$L = 11$	$L = 12$	$L = 13$
$\delta^{\text{high}}_{i,t-1 \text{ to } t-L}$	-0.90	-0.93	-0.96	-1.11	-1.66	.	-2.85	-3.08	-4.53*	-5.98**
	(0.712)	(1.485)	(1.753)	(1.996)	(2.210)	.	(2.374)	(2.224)	(2.350)	(2.778)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-L}$	1.47**	3.03***	3.71***	4.20***	4.53***	.	3.94**	3.95**	3.65*	3.25
	(0.611)	(0.864)	(1.040)	(1.215)	(1.328)	.	(1.809)	(1.878)	(1.904)	(2.140)
$CR\_GAP_{i,t-1 \text{ to } t-L}$	0.81***	0.71***	0.60***	0.52***	0.44***	.	0.10	0.09	0.10	0.11
	(0.031)	(0.069)	(0.080)	(0.077)	(0.083)	.	(0.104)	(0.108)	(0.112)	(0.130)
$\log GDP_{i,t-1 \text{ to } t-L}$	-1.20	0.49	1.19	1.33	0.32	.	0.28	0.35	0.12	-0.26
	(1.970)	(2.021)	(2.477)	(2.878)	(3.173)	.	(2.901)	(2.818)	(3.092)	(3.378)
$\Delta PD/GDP_{i,t-1 \text{ to } t-L}$	-0.57**	-1.13***	-1.55***	-1.83***	-1.88***	.	-1.79***	-1.62**	-1.45*	-1.27
	(0.245)	(0.366)	(0.461)	(0.516)	(0.540)	.	(0.671)	(0.743)	(0.877)	(1.027)
$POLCOMP_{i,t-1 \text{ to } t-L}$	-0.10	0.11	0.33	0.50	0.60	.	0.55	0.53	0.46	0.42
	(0.356)	(0.513)	(0.576)	(0.613)	(0.637)	.	(0.722)	(0.680)	(0.613)	(0.594)
$INFLATION_{i,t-1 \text{ to } t-L}$	-0.67*	-0.50	-0.45	-0.48	-0.56	.	0.02	0.07	0.14	0.19
	(0.392)	(0.416)	(0.449)	(0.479)	(0.462)	.	(0.299)	(0.282)	(0.268)	(0.276)
$INTRATE_{i,t-1 \text{ to } t-L}$	0.17	0.13	0.03	-0.06	-0.16	.	-0.13	-0.12	-0.13	-0.14
	(0.195)	(0.188)	(0.223)	(0.294)	(0.356)	.	(0.369)	(0.343)	(0.324)	(0.309)
Num of Obs.	821	836	851	864	875	.	903	906	907	908
Adj. R^2	0.678	0.542	0.422	0.337	0.274	.	0.0839	0.0732	0.0712	0.0715

Table 4: **Robustness: Low volatility and risk-taking**

This table presents different robustness tests for the link between low volatility and risk-taking behavior. The first three columns present the results when alternative proxies of risk-taking are used. In Column I, we use credit growth ($\Delta logCR$) calculated as the difference of the log-credit-to-GDP ratio. In Columns II and III, we use the credit-to-GDP ratio gap and credit growth as dependent variables employing annual aggregate bank loan data from Schularick and Taylor (2012). The BIS sample covers 35 countries and spans 1960–2010, whereas the Schularick and Taylor (2012) sample covers 14 developed countries for 1870–2010. In Column IV, we exclude the lag of the dependent variable, in Column V, we remove all of the control variables, and in Column VI, we include the credit trend. In Column VII, volatility is calculated by employing monthly returns up to end-year instead of mid-year. In Column VIII, we measure volatility as the sum of absolute monthly returns instead of standard deviation. Column IX reports the results when the smoothing parameter of the HP filter is set to 6 instead of 100. Finally, in Column X, we check whether our main results are still present if observations after 2007 are excluded from the analysis. 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 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.

	$Y_{i,t} = \Delta logCR^{\text{BIS}}_{i,t}$	$Y_{i,t} = CR\_GAP^{\text{ST}}_{i,t}$	$Y_{i,t} = \Delta logCR^{\text{ST}}_{i,t}$	No Lagged Dep. Var.	No Control Vars.	Cr. Trend Included	12M	ABS	$\lambda = 6$	2008 Crisis Excluded
	I	II	III	IV	V	VI	VII	VIII	IX	X
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$	0.02	-0.01***	-0.91	-0.54	-3.09*	-0.98	0.17	-2.18	-0.69	-1.83
	(0.407)	(0.003)	(0.932)	(1.887)	(1.872)	(2.000)	(2.260)	(2.870)	(0.998)	(2.268)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$	0.97***	0.01**	1.32**	4.69***	3.36***	3.21**	5.78***	6.17***	1.96***	3.59**
	(0.281)	(0.004)	(0.544)	(1.147)	(1.075)	(1.356)	(1.727)	(1.964)	(0.741)	(1.543)
$Y_{i,t-1 \text{ to } t-5}$	0.13	0.44***	0.22**			0.39***	0.45***	0.45***	-0.16	0.38***
	(0.142)	(0.101)	(0.092)			(0.094)	(0.103)	(0.084)	(0.145)	(0.087)
$\log GDP_{i,t-1 \text{ to } t-5}$	-1.09*	-0.00	-0.64	1.92		12.31**	1.65	0.35	-1.14	-1.88
	(0.655)	(0.010)	(1.029)	(3.686)		(5.251)	(2.798)	(3.075)	(1.450)	(3.450)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$	-0.55***	-0.00	-0.15	-2.36***		-1.87***	-1.86***	-1.89***	-0.60***	-2.10***
	(0.112)	(0.001)	(0.098)	(0.614)		(0.537)	(0.545)	(0.524)	(0.221)	(0.607)
$POLCOMP_{i,t-1 \text{ to } t-5}$	0.18**	0.00	0.20	0.25		1.22	0.77	0.54	0.22	0.94
	(0.090)	(0.001)	(0.129)	(0.736)		(0.926)	(0.574)	(0.665)	(0.251)	(0.679)
$INFLATION_{i,t-1 \text{ to } t-5}$	-0.37**	0.00***	0.66**	-0.73		-0.89**	-0.72	-0.60	-0.31	-0.59
	(0.173)	(0.001)	(0.264)	(0.482)		(0.446)	(0.450)	(0.474)	(0.195)	(0.441)
$INTRATE_{i,t-1 \text{ to } t-5}$	0.03	0.00**	0.56	-0.08		-0.33	-0.18	-0.15	-0.16	-0.17
	(0.048)	(0.002)	(0.346)	(0.338)		(0.436)	(0.364)	(0.361)	(0.167)	(0.330)
$\tau_{i,t-1 \text{ to } t-5}$						-0.05***				
						(0.017)				
Num of Obs.	955	877	955	888	1,080	875	879	875	875	792
Adj. R^2	0.177	0.230	0.139	0.178	0.0655	0.317	0.274	0.279	0.0696	0.274

Table 5: **Volatility channels and financial crises: sub-periods**
This table presents the results for the regression equation introduced in (3) for different sub-periods. The early (1800–1913), postwar (1946–2010), and Great Moderation (1985–2006) periods are considered. 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 1. 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
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.20	-0.76	0.27**	0.10
	(0.128)	(0.499)	(0.129)	(0.231)
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	0.31***	-0.86	0.30**	0.35***
	(0.115)	(0.742)	(0.123)	(0.128)
$C_{i,t-1 \text{ to } t-5}$	-7.86***	-11.58***	-7.46**	-5.75*
	(2.039)	(1.515)	(3.129)	(3.189)
$\log GDP_{i,t-1 \text{ to } t-5}$	0.07	2.64	0.26	-0.10
	(0.229)	(4.882)	(0.303)	(0.271)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$	-0.07***	-0.14**	-0.06***	-0.06
	(0.026)	(0.071)	(0.023)	(0.060)
$POLCOMP_{i,t-1 \text{ to } t-5}$	-0.09*	0.14	-0.11*	0.03
	(0.048)	(0.283)	(0.060)	(0.172)
$INFLATION_{i,t-1 \text{ to } t-5}$	0.02	0.03	0.01	0.02
	(0.011)	(0.109)	(0.009)	(0.012)
Num of Obs.	2,134	239	1,595	819
Pseudo R^2	0.106	0.163	0.100	0.150
Marginal effects (%)				
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.6593	-3.0918	0.7703	0.1959
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	1.0113	-3.5189	0.8773	0.6612

Table 6: **Stock market and currency crises**
This table presents the results for the regression equation introduced in (3). In Columns I to IV, the dependent variable is a dummy variable that takes the value 1 in the first year of a stock market crises. Similarly, the results for currency crises are presented in Columns V-VIII. δ^{high} and δ^{low} are high and low volatility introduced in (2). All of the control variables are defined in Table 1. 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.

	$C_{i,t}^{\text{Stock}}$				$C_{i,t}^{\text{Currency}}$			
	I	II	III	IV	V	VI	VII	VIII
$\sigma_{i,t-1 \text{ to } t-5}$	0.05*	0.02			0.01	-0.00		
	(0.027)	(0.036)			(0.023)	(0.038)		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$			0.15***	0.15*			0.03	-0.03
			(0.056)	(0.085)			(0.078)	(0.097)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$			0.22**	0.20**			0.06	0.06
			(0.096)	(0.096)			(0.069)	(0.070)
$C_{i,t-1 \text{ to } t-5}$	-4.80***	-4.92***	-4.60***	-4.91***	-0.95	-1.52*	-1.22	-1.89**
	(0.719)	(0.700)	(0.784)	(0.770)	(0.707)	(0.785)	(0.767)	(0.835)
$\log GDP_{i,t-1 \text{ to } t-5}$		0.04		0.00		-0.33**		-0.46***
		(0.167)		(0.202)		(0.131)		(0.132)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$		0.00		0.00		0.01		0.01
		(0.008)		(0.009)		(0.009)		(0.008)
$POLCOMP_{i,t-1 \text{ to } t-5}$		0.00		0.01		-0.01		0.01
		(0.031)		(0.029)		(0.033)		(0.035)
$INFLATION_{i,t-1 \text{ to } t-5}$		0.01		0.01		-0.00		-0.01
		(0.010)		(0.009)		(0.009)		(0.008)
Num of Obs.	3,375	3,144	2,846	2,703	3,606	3,323	2,972	2,785
Pseudo R^2	0.0571	0.0593	0.0597	0.0635	0.0147	0.0237	0.0202	0.0311
Marginal effects (%)								
$\sigma_{i,t-1 \text{ to } t-5}$	0.458	0.175			0.08	-0.002		
$\delta^{\text{high}}_{i,t-1 \text{ to } t-5}$			1.367	1.363			0.209	-0.233
$\delta^{\text{low}}_{i,t-1 \text{ to } t-5}$			1.931	1.786			0.413	0.427

Table 7: **Stock market crises: different lag lengths**

This table presents the results for the regression equation introduced in (3) for stock market crises for different lag lengths (L). The dependent variable is a dummy variable that takes the value 1 in the first year of a stock market crisis. δ^{high} and δ^{low} are high and low volatility introduced in (2). Control variables are introduced in Table 1. All of the specifications include decade and region 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.

Dep. Var.: $C^{\text{Stock}}_{i,t}$	$L=1$	$L=2$	$L=3$	$L=5$	$L=7$	$L=8$	$L=11$
$\delta^{\text{high}}_{i,t-1 \text{ to } t-L}$	0.11*	0.16**	0.16*	0.15*	0.18	0.12	0.11
	(0.066)	(0.077)	(0.084)	(0.085)	(0.118)	(0.106)	(0.095)
$\delta^{\text{low}}_{i,t-1 \text{ to } t-L}$	0.06	0.08	0.12	0.20**	0.22**	0.19**	0.15*
	(0.089)	(0.091)	(0.087)	(0.096)	(0.094)	(0.090)	(0.081)
$C_{i,t-1 \text{ to } t-L}$		-3.58***	-3.73***	-4.91***	-5.64***	-4.32***	-3.95***
		(0.592)	(0.571)	(0.770)	(1.110)	(0.743)	(0.886)
$\log GDP_{i,t-1 \text{ to } t-L}$	0.05	0.07	-0.00	0.00	-0.03	-0.05	-0.08
	(0.191)	(0.186)	(0.180)	(0.202)	(0.211)	(0.196)	(0.194)
$\Delta PD/GDP_{i,t-1 \text{ to } t-L}$	-0.02	-0.02	-0.00	0.00	0.00	0.00	-0.00
	(0.012)	(0.016)	(0.006)	(0.009)	(0.009)	(0.008)	(0.011)
$POLCOMP_{i,t-1 \text{ to } t-L}$	-0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.028)	(0.033)	(0.028)	(0.029)	(0.033)	(0.030)	(0.029)
$INFLATION_{i,t-1 \text{ to } t-L}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.009)	(0.007)	(0.006)	(0.009)	(0.008)	(0.007)	(0.008)
Num of Obs.	2,273	2,624	2,657	2,703	2,745	2,765	2,811
Pseudo R^2	0.0364	0.0735	0.0619	0.0635	0.0579	0.0403	0.0331
Marginal effects (%)							
$\delta^{\text{high}}_{i,t-1 \text{ to } t-L}$	1.2462	1.3394	1.4092	1.3632	1.5924	1.0933	1.0806
$\delta^{\text{low}}_{i,t-1 \text{ to } t-L}$	0.6874	0.6857	1.0487	1.7858	1.9699	1.7715	1.3952

Table 8: **Robustness: Volatility channels 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 Columns I and II, we use alternative definitions of high and low volatility. 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, volatility is calculated by employing monthly returns up to December (end year) instead of mid-year returns. In Column IV, we measure volatility as the sum of absolute monthly returns. In Column V and VI, we include the interest rate and credit-to-GDP gap as control variables, respectively. In Column VII, we repeat the analysis without any fixed effects. In Column VIII, we report the results from OLS regressions. In Column IX, we present the results when the lag of the dependent variable is excluded. In Column X, we include the trend (τ) estimated through an HP filter in the regression along with high and low volatility variables. In Column XI, we report the results when the smoothing parameter of the HP filter is set to 100 instead of 5000. In Column XII, we check whether our main results are still present if world wars, great depression, and 2008 crises are excluded from the analysis. Finally, in Column XIII, 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 variables introduced in Table 1 are included in all of the specifications. 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.

	Historical Mean	Band	12M	ABS	Int. Rates Included	Credit Included	No FEs	OLS	No lagged Dep. Var.	Trend Included	$\lambda = 100$	Wars & 2008 excluded	Merged Data
Dep. Var.: $C_{i,t}^{\text{Banking}}$	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII
$\delta_{i,t-1 \text{ to } t-5}^{\text{high}}$	0.17*	0.23*	0.08	0.21	0.35	0.31	0.15	0.01	0.14	0.23	0.04	0.29	0.12
	(0.088)	(0.124)	(0.129)	(0.162)	(0.226)	(0.261)	(0.105)	(0.006)	(0.131)	(0.151)	(0.178)	(0.196)	(0.137)
$\delta_{i,t-1 \text{ to } t-5}^{\text{low}}$	0.29**	0.49**	0.21**	0.35**	0.48***	0.51***	0.24**	0.01**	0.22**	0.41**	0.37**	0.28**	0.27**
	(0.118)	(0.217)	(0.103)	(0.144)	(0.154)	(0.137)	(0.094)	(0.006)	(0.099)	(0.206)	(0.184)	(0.139)	(0.115)
$C_{i,t-1 \text{ to } t-5}$	-8.34***	-8.29***	-7.90***	-7.85***	-7.48**	-7.98**	-3.79**	-0.31***		-7.86***	-7.62***	-8.62***	-6.53***
	(1.969)	(1.953)	(1.881)	(2.020)	(3.583)	(4.061)	(1.931)	(0.067)		(2.062)	(1.877)	(2.587)	(1.775)
$\log GDP_{i,t-1 \text{ to } t-5}$	0.18	0.16	0.06	0.06	0.08	0.16	0.05	0.01	0.09	0.07	0.03	0.18	0.11
	(0.195)	(0.178)	(0.221)	(0.230)	(0.377)	(0.516)	(0.257)	(0.007)	(0.176)	(0.229)	(0.213)	(0.266)	(0.230)
$\Delta PD/GDP_{i,t-1 \text{ to } t-5}$	-0.07***	-0.07***	-0.06**	-0.07**	-0.07**	-0.04	-0.03**	-0.00**	-0.08***	-0.07***	-0.07**	-0.07**	-0.07***
	(0.025)	(0.026)	(0.025)	(0.027)	(0.034)	(0.059)	(0.013)	(0.001)	(0.020)	(0.024)	(0.027)	(0.034)	(0.025)
$POLCOMP_{i,t-1 \text{ to } t-5}$	-0.08*	-0.09**	-0.09**	-0.09*	-0.19**	-0.10	-0.06	-0.00*	-0.07*	-0.08*	-0.09*	-0.10*	-0.08*
	(0.047)	(0.043)	(0.043)	(0.047)	(0.088)	(0.108)	(0.049)	(0.002)	(0.041)	(0.048)	(0.047)	(0.052)	(0.048)
$INFLATION_{i,t-1 \text{ to } t-5}$	1.80*	1.79*	0.02*	0.02*	0.00	0.04**	0.01*	0.00*	0.01	0.02*	0.02	0.01	0.02*
	(0.952)	(0.939)	(0.011)	(0.011)	(0.015)	(0.015)	(0.005)	(0.001)	(0.009)	(0.014)	(0.011)	(0.012)	(0.010)
$INTRATE_{i,t-1 \text{ to } t-5}$					-0.02								
					(0.020)								
$CR\_GAP_{i,t-1 \text{ to } t-5}$						0.04**							
						(0.018)							
$\tau_{i,t-1 \text{ to } t-5}$										-0.06			
										(0.094)			
Num of Obs.	2,168	2,164	2,181	2,134	1,205	1,047	2,886	2,886	2,134	2,134	2,134	1,677	2,134
Pseudo R^2	0.102	0.103	0.102	0.105	0.123	0.114	0.0292	0.0410	0.0665	0.107	0.103	0.143	0.0967