

Stability of Expectations and Severity of Crises

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Abstract

We show that the severity of banking and debt crises is negatively related to the volatility of GDP growth expectations. Series of expectations are built by using a stochastic-gain learning algorithm whose predictions match survey data on output growth expectations well. We construct several measures of severity of crises that capture output growth losses associated with crises. Our empirical analysis addresses Hyman Minsky's theoretical conjecture (part of his so-called Financial Instability Hypothesis) that macroeconomic stability is conducive to high leverage, which in turn makes a crisis more severe once it happens.

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1 Introduction

This paper analyzes the empirical validity of one of the corollaries of the so-called Minsky's Financial Instability Hypothesis (FIH), according to which the further back in time the last crisis occurred, the more severe is the new crisis when it comes. The rationale of the hypothesis is that the further into the past a former crisis is situated, the more agents become optimistic and confident in their own forecasts, which drives them to borrow more. Therefore, if a crisis occurs after a long period of stability, the economy will be highly leveraged, leading to a greater disruption of the structure of contracts, hence implying severe losses in the real economy.

We measure overconfidence by constructing and using a measure of stability of expectations on output growth. The underlying idea is that, consistent with the literature on learning in macroeconomics, when agents become more confident about their forecasts, the size of forecasts' updates becomes smaller. Hence, more confidence in forecasts is associated with more stable expectations. On the other hand, the severity of a crisis is measured in different ways that seek to capture the output losses associated with crises. We describe the methodology for measuring severity of crises in section 2.

Consistent with the FIH, we find that banking and debt crises –crises that involve massive defaults– are more severe when they are preceded by more stable expectations. This result holds in the pooled data and in the panel data analysis with the inclusion of fixed effects.

When we include currency and inflation crises, the correlation between stability of expectations and severity of crises becomes not significantly different from zero. This result is not surprising. Governments' incentives to resort to seigniorage are greater when the availability of credit to the private sector is more limited. Also, governments' access to credit is negatively related to volatility of expectations. Therefore, higher volatility of expectations should be associated with a more intense use of seigniorage, implying a positive relationship between volatility of expectations and severity of currency and inflation crises.

Thus, our results show that, even though the more volatile countries have a higher frequency of overborrowing crises, those crises are more severe when they

occur after periods of greater stability.

1.1 Related literature

Our paper is mostly related to the literature on endogenous financial fragility, especially to the work of Hyman Minsky (1975, 1986, 1992) and his Financial Instability Hypothesis (FIH), also described by Kindleberger (1978). The FIH is a theory of the impact of debt on system behavior that also incorporates the manner in which debt is validated. It draws upon the credit view of money and finance developed by Joseph Schumpeter (1934). One of its corollaries is that over periods of prolonged prosperity, an economy transits from financial relations that make for a stable system to financial relations that make for an unstable system. This dynamic is characterized by a build-up of leverage. Hence, the more prolonged the period of prosperity, the higher the likelihood of a financial crisis, and the more severe the crisis if it occurs. The transmission channel that leads to endogenous financial fragility is overconfidence. Our empirical analysis addresses this hypothesis by investigating how overconfidence, measured as the inverse of a measure of volatility of expectations, is related to the depth of financial crises.

The backdrop of our analysis is a world in which there may be behavioral agents subject to fads, fashions, overconfidence, and related psychological biases that might lead to overborrowing and overlending. There is a large literature that documents and models such behaviors, like Daniel, Hirshleifer, and Subrahmanyam (1998), Hirshleifer (2001), Odean (1998), Thaler (1991), Shiller (2000), and Shleifer (2000), among others. We do not investigate the causes of the emergence of overconfidence, but we study its impact on the severity of financial crises.

Our paper is also related to the literature on the consequences of the interaction of leverage and expectations for financial instability. Geanakoplos (2009) and Fostel and Geanakoplos (2008, 2012) introduce a general equilibrium analytical framework with heterogeneous agents, incomplete markets, and endogenous collateral, that illustrates how the interaction between endogenous leverage and news contributes to understanding how a crisis propagates through the financial side to the real economy. Our empirical analysis relies on the existence of a leverage channel, in which optimistic expectations lead to higher leverage that, in the event

of a crisis, implies a deeper propagation of the disruptions in the financial side to the real economy. This propagation is also accelerated by changes in expectations from being optimistic to pessimistic.

Finally, our paper is related to the empirical literature on the extent and determinants of the severity of crises. Part of this literature focuses on measuring the depth of post-crises downturns, typically as the deviation of GDP from a trend prior to the crisis (Bordo et al (2001), Hutchison and Noy (2005), Jonung and Hagberg (2010)). Berkman et al. (2012) measure crisis' depth as the difference between actual post-crises GDP growth and the pre-crisis forecast. They find that the severity of crises is positively associated with the degree of leverage in the domestic financial system, credit growth, and amount of short-term debt. Aizenman and Noy (2012) analyze the importance of several dimensions for the severity of crises using three different measures of severity: output losses as calculated by Laeven and Valencia (2012), ratio of non-performing loans over GDP, and fiscal costs. The recent global financial crisis has also triggered a wave of empirical research. Mian and Sufi (2010) show that household leverage is a powerful statistical predictor of the severity of the 2007 to 2009 recession across U.S. counties. Cecchetti et al (2012) examine the importance of the pre-crisis conditions for the depth of the downturn that followed this crisis. To our knowledge, there is no paper that empirically analyzes how overconfidence, measured by the inverse of volatility of expectations, affects the severity of financial crises.

2 A theoretical analysis on volatility of output growth expectations

This section illustrates how the perception of a more stable economy is associated with lower volatility of output growth expectations, within the framework of models with learning for formation of expectations. In either Bayesian or non-Bayesian learning models, changes in agents' output growth expectations are smaller when they believe that observed changes in output growth are mostly of a transitory nature. Furthermore, the smaller updates reinforce the general perception that the share of output variance due to transitory relative to permanent shocks has

increased, which in turn leads to even smaller updates of forecasts.

2.1 Volatility of output growth expectations under Bayesian learning

Assume that the growth rate of output at time t , g_t^y is given by

$$g_t^y = g_t + z_t - z_{t-1} \quad (1)$$

where the g shocks are of a permanent (cumulative) nature, and the z shocks are of a transitory nature.

Suppose that transitory shocks z_t follow an AR(1) process:

$$z_t = \rho_z z_{t-1} + \epsilon_t^z \quad (2)$$

with $|\rho_z| \in (0, 1)$, $\epsilon_t^z \sim N(0, \sigma_z^2)$, where ρ_z and σ_z^2 represent the persistence and the variance of the transitory shocks, respectively.

Also, suppose that cumulative permanent shocks g_t are described by

$$g_t = (1 - \rho_g)\mu_g + \rho_g g_{t-1} + \epsilon_t^g \quad (3)$$

with $|\rho_g| \in (0, 1)$, $\epsilon_t^g \sim N(0, \sigma_g^2)$, where μ_g is the steady state growth rate of output, and ρ_g and σ_g^2 represent the persistence and the variance of the permanent shocks, respectively.

Suppose that at time t the agents observe the aggregate shock g_t^y but they do not observe the precise decomposition of the shock. Instead, the best they can do is to use past information and the signal they receive (i.e. the aggregate shock), in order to infer what share of the shock is permanent and what it is transitory. Assuming normality for the distribution of errors, the optimal strategy to decompose the aggregate shock will be to use a linear estimator, that is, a Kalman filter that results in posterior beliefs according to

$$a_t = k_1 a_{t/t-1} + k_2 g_t^y \quad (4)$$

where $a_t = E(\alpha_t/I_t) = [\tilde{z}_t \ \tilde{z}_{t-1} \ \tilde{g}_t]'$, $\alpha_t = [z_t \ z_{t-1} \ g_t]'$, and k_1 and k_2 are the Kalman coefficients that determine the mapping of prior beliefs $a_{t/t-1}$ and signals into posterior beliefs of transitory and permanent components of the aggregate shock. The Kalman coefficients depend on the parameters that govern the productivity processes g_t and z_t .

We can write

$$\alpha_t = T\alpha_{t-1} + c + R\eta_t \quad (5)$$

where

$$T = \begin{bmatrix} \rho_z & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho_g \end{bmatrix}; c = \begin{bmatrix} 0 \\ 0 \\ (1 - \rho_g)\mu_g \end{bmatrix}; R = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}; \eta_t \begin{bmatrix} \epsilon_t^z \\ \epsilon_t^g \end{bmatrix}$$

with $\eta_t \sim N(0, Q)$, $Q = \begin{bmatrix} \sigma_z^2 & 0 \\ 0 & \sigma_g^2 \end{bmatrix}$.

The Kalman filters are

$$k_1 = I - PZ'(ZPZ')^{-1}Z \quad (6)$$

$$k_2 = PZ'(ZPZ')^{-1} \quad (7)$$

where P is the steady state covariance matrix of estimation errors $P_t = E[(\alpha_t - a_t)(\alpha_t - a_t)']$, calculated following the Riccati equation as:

$$P = TPT' - TPZ'(ZPZ')^{-1}ZPT' + RQR' \quad (8)$$

Also, the prior belief is given by

$$a_{t/t-1} = Ta_{t-1} + c \quad (9)$$

The Kalman coefficients used for updating forecasts produce the following result:

Result 1 *The larger $\frac{\sigma_z^2}{\sigma_z^2}$, the larger the share of g_t^y attributed to \tilde{g}_t .*

In the Bayesian context, the parameters that govern the productivity processes are recursively updated when a new signal arrives. As a consequence, we obtain

the following result:¹

Result 2 If $\frac{\tilde{g}_t - \tilde{\mu}_g}{g_t^y} > \frac{\tilde{z}_t}{g_t^y}$, then $\frac{\sigma_{g/t}^2}{\sigma_{z/t}^2} > \frac{\sigma_{g/t-1}^2}{\sigma_{z/t-1}^2}$

Result 2 establishes that when the share of the deviation between the belief of the permanent component of the aggregate shock in period t and the perceived mean is greater than the share of the belief of the transitory component, then the perceived relative variance of the permanent component conditional on the new information increases (with respect to the relative variance conditional on the old information set).

Definition 1 – Change in expectations. $CE_{t-1,t}$ is the change in output growth expectations from period $t - 1$ to t ,

$$CE_{t-1,t} = E_t g_{t+1}^y - E_{t-1} g_t^y$$

For the productivity processes and the forecasts update process defined, we obtain

$$CE_{t-1,t} = (1 - \rho_g)(\mu_{g/t} - \mu_{g/t-1}) + \rho_g(\tilde{g}_t - \tilde{g}_{t-1}) + (\rho_z - 1)(\tilde{z}_{t/t} - \tilde{z}_{t-1/t-1}) \quad (10)$$

That is, expectations may change due to three sources: changes in the belief about the steady state growth of permanent productivity, changes in the belief about the permanent shock, and changes in the belief about the contemporaneous transitory shock.

Definition 2 – Stability of expectations. $SOE(j, J)$ is a measure of the stability of expectations between periods j and J :

$$SOE(j, J) = \frac{1}{J - j} \sum_{t=j}^J CE_{t-1,t}$$

¹Note that with Bayesian learning, past beliefs on the transitory shock \tilde{z}_{t-1} are also updated.

A larger value of *SOE* means higher volatility of expectations. Next proposition illustrates the fact that a long stream of good signals leads agents to believe that the economy is located on a high μ_g path, with deviations from that path being most likely transitory.

Proposition 1 *For the Bayesian learning process, more output growth stability implies smaller SOE*

Proof 1 *By result 1, $(\mu_{g/t} - \mu_{g/t-1})$ and $(\tilde{g}_t - \tilde{g}_{t-1})$ are decreasing in output growth stability, what leads to smaller CE hence smaller SOE. Result 2 accelerates the effect of more stability decreasing SOE*

2.2 Volatility of output growth expectations under non-Bayesian learning

The result established in proposition 1 can also be obtained in a non-Bayesian learning framework that satisfies a set of “desirable” (in the sense of being minimum deviations from rationality) conditions.

Suppose that the agents either do not know the process that govern the productivity processes or that they know it but do not use that information in order to forecast future output growth. They do know that there are two types of output growth shocks, permanent and transitory. Instead of using their beliefs of the parameters that govern productivity to form new beliefs by using a Kalman filter, suppose that they follow a simple rule, called stochastic-gain learning (SGL). If forecast errors are small, the individual adjusts her expectations by using a decreasing gain parameter. If forecast errors are large, the individual suspects that there was a change of regime and uses a constant gain parameter, which assigns more importance to information from the present. This algorithm is introduced in the literature by Sargent (1993), and further explored by Marcet and Nicolini (2003) and Milani (2007).

Let g_t^y be the growth rate of output at time t and let E_t denote the expectation over variables at time t . Analytically, SGL is represented by

$$E_t g_{t+1}^y = E_{t-1} g_t^y + \kappa_t (g_t^y - E_{t-1} g_t^y) \quad (11)$$

with

$$\kappa_t = \begin{cases} 1/t & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1} g_{t-s}^y|) < v_t^y \\ \kappa & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1} g_{t-s}^y|) \geq v_t^y \end{cases} \quad (12)$$

where κ_t is the gain parameter that determines how expectations respond to forecast errors, S is the relevant time horizon for comparing recent forecast errors with historical forecast errors, and v_t^y is the mean absolute deviation of historical forecast errors, which is recursively updated. When the agent switches back to a decreasing-gain parameter, the parameter is reset to $\frac{1}{\kappa^{-1}+t}$, with $t = 1$ after the switch.

SGL satisfies desirable lower bounds on rationality (introduced by Sargent (1993), proved in Marcet and Nicolini (2003)). Let $p^{\epsilon, T}$ be the probability that the perceived errors in a sample of T periods will be within $\epsilon > 0$ of the rational expectations error. Then, SGL satisfies:

Definition 3 *Asymptotic rationality (AR):* $p^{\epsilon, T}$ converges to 1 for T large, $\forall \epsilon > 0$

Definition 4 *Epsilon-Delta Rationality (EDR):* for (ϵ, δ, T) , $p^{\epsilon, T} \geq 1 - \delta$, for $\delta > 0$

Definition 5 *Internal consistency (IC):* After T periods, the average perceived error using the rule for κ_t is smaller than under any alternative learning rule for κ_t (studied only for “moderately high” T)

AR implies asymptotic good forecasts, while EDR and IC imply good forecasts along the transition.

With SGL, we have

$$CE_{t-1,t} = \kappa_t (g_t^y - E_{t-1} g_t^y) \quad (13)$$

From the definition of κ_t , we infer that the more stability leads to a lower κ_t . Hence, a long stream of consecutive similar signals will also be conducive of a reduction of volatility of expectations. Trivially, proposition 1 also holds for the SGL process.

Proposition 2 *For the SGL process, more output growth stability implies smaller SOE*

3 Data on GDP growth expectations and financial crises

We analyze the relationship between several measures of severity of crises and a measure of stability of expectations. In this section we present the data we use to construct those measures.

3.1 Crises and their severity

Dates of crises

The preliminary analysis we present in this paper uses the crises panel datasets from Laeven and Valencia (2012) and Reinhart and Rogoff (2009).

Laeven and Valencia (2012) extend and build on widely used databases by Caprio et al (2005) and Laeven and Valencia (2008, 2010). Their database includes all systemic banking, currency, and sovereign debt crises during the period 1970-2011. Their definition of a banking crisis is broad: There is a banking crisis if a country's corporate and financial sectors experience a large number of defaults and if financial institutions and corporations face great difficulties repaying contracts on time. Unlike Caprio et al. (2005) or Reinhart and Rogoff (2009), they exclude banking system distress events that affect isolated banks but are not systemic in nature. Their definition of a currency crisis builds on Frankel and Rose (1996)'s approach. They define a currency crisis as a nominal depreciation of the currency vis-à-vis the U.S. dollar of at least 30 percent and that is also at least 10 percentage points higher than the rate of depreciation in the year before. Finally, they date episodes of sovereign debt default and restructuring by relying on information from Beim and Calomiris (2001), World Bank (2002), Sturzenegger and Zettelmeyer (2006), IMF Staff reports, and reports from rating agencies.

Reinhart and Rogoff (2009)'s more extensive database also includes data on inflation crises. They mark an inflation crisis if the annual rate of inflation exceeds x percent. They present data for $x = \{20, 40\}$. We use $x = 40$. Two types of events

mark the beginning of a banking crisis: (i) a bank run that leads to the closure, merging, or takeover by the public sector of one or more financial institutions, and (ii) if there are no runs, the closure, merging, take-over, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions (p.11). A sovereign debt crisis is marked when there is an external or domestic sovereign default. Finally, a currency crisis is marked when there is an annual depreciation versus the US dollar of 15 percent or more. From this database, we use data since 1950.²

Severity of crises

The metric we use for calculating the severity of crises is output growth loss. This is an incomplete measure of the cost of crises, with several shortcomings. Firstly, it does not capture the cost of crises associated to redistribution of income. Secondly, as the literature on jobless recovery indicates, output growth may recover with no recovery in employment. It is, however, an important metric of losses in the real economy.³ We estimate our model using four alternative measures of severity of crises associated to output growth losses.

Our first measure of severity follows the IMF (1998)'s methodology. The cost of a crisis is measured as the output loss associated with lower after-crisis growth rate of output. Formally, the output growth loss is calculated as

$$Sev(t_0) = \sum_{t=t_0}^{t_n} (\tilde{g}_{t_0}^y - g_t^y) \quad (14)$$

where $Sev(t_0)$ stands for severity of crisis that starts in period t_0 , t_n is the end date of the crisis, $\tilde{g}_{t_0}^y$ is the GDP growth trend in the years preceding the crisis, calculated by applying the Hodrick-Prescott filter, and g_t^y is the growth rate of GDP in period t . IMF (1998) uses a three-year trend for calculating $\tilde{g}_{t_0}^y$. The existing literature has pointed out that GDP growth before a crisis is not an

²We choose this period to isolate our results from the effects of the First and Second World Wars on severity of crises.

³Other measures for severity of crises utilized in the literature are (i) Fiscal costs: bank restructuring costs defined as gross fiscal expenditures directed to restructuring the financial sector (% of GDP); and (ii) Peak of Non-Performing Loan level reached (% of total loans).

accurate measure of sustainable GDP growth (cf. Boyd et al., 2005). Calculating the output growth trend by using a longer time-span may mitigate those problems. In this respect, Bordo et al. (2001) use a five-year trend. We follow the same approach as Bordo et al. (2001). We use GDP data from Barro and Ursúa Macroeconomic Data Set (2010). The start date of the crisis comes from Laeven and Valencia (2012) or Reinhart and Rogoff (2009). The end of the crisis is assigned to the year in which the GDP growth rate reaches the pre-crisis GDP growth trend. This strategy for dating the crisis ending date may lead to an overestimation of output growth losses. This is the case when a crisis is associated with a structural change that implies a permanent reduction in the growth rate of output. This effect is noticeable in our sample. We discuss its consequences in the interpretation of the results.

Our second measure addresses the problem of overestimation that the above methodology may suffer by using a different criterion to date the end of a crisis. We simply use the date of resolution assigned by either Reinhart and Rogoff (2009) or Laeven and Valencia (2012) to each crisis. The crisis resolution may or may not be accompanied of an output growth recovery. Instead, depending on the type of crisis, resolution involves issues like the restructuring of financial institutions, corporations, government debt, return to low exchange rate depreciations, or low inflation levels.

Our third measure is the change in GDP between the year before and the year after the crisis. This criterion may also overestimate the output losses associated with crises, due to the same issue discussed in the description of our first measure, i.e., output growth tends to be unsustainably high in the year before the crisis.

Our fourth measure addresses the overestimation bias of the third measure by calculating the difference between the GDP growth five-year trend before the crisis and the GDP after the crisis. Even though the five-year trend will more likely also be above sustainable output growth (otherwise a financial crisis would have been less likely), the problem of overestimation is less severe than in the case of the third measure.

The online appendix provides a database with all the measures of severity, Table 1 shows the correlations among the different measures. As expected, the measure calculated following the IMF methodology has the lowest correlation with

the three others, because by construction it is the one that exacerbates the most the overestimation of output growth loss.

3.2 Expectations

The coverage of survey data on GDP growth expectations is increasing, both in time-length and number of countries being considered. However, available data is still not sufficient for the empirical analysis we pursue in this paper. Therefore, we need to build data on GDP growth expectations.

We depart from the following questions: What is a good algorithm for representing how agents form expectations on GDP growth? What are the data requirements to create a series of expectations by using such an algorithm?

The first question is of a purely empirical nature, and can be addressed by determining what theoretical mechanism for formation of expectations has a better match with actual expectations. We can tackle that problem by performing a comparison between how different theoretical mechanisms match data on actual GDP growth expectations taken from the Survey of Professional Forecasters (SPF) of Consensus Forecasts.

We take three different theoretical mechanisms for formation of expectations. These mechanisms are perfect foresight, Kalman Filter learning, and stochastic-gain learning (SGL). Under perfect foresight, the expected growth rate of GDP is computed as the actual growth rate of GDP. Under Kalman filter learning, the expected growth rate of GDP is a convex combination of prior beliefs and the observed GDP growth rate, as described in section 2. Under SGL, the agent updates forecasts by using a gain parameter that depends on the size of previous forecasts errors, as explained in section 2 as well. Data requirements for perfect foresight and SGL are minimum: we only need a series of GDP growth, and we need to impute an initial forecast for the first period of the sample. With Kalman filter learning, we also need to estimate or assume values for the moments that govern the productivity processes.⁴

The SPF offers quarterly data on GDP growth expectations since 1999. We calculate the average sum of squared differences between actual expectations and the-

⁴In the calculations that we perform, we assign the perfect information model parameters to the imperfect information rational expectations mechanism, as in Guzman (2013).

oretical expectations for every mechanism, for all the countries available in the SPF sample. Unsurprisingly, we obtain that in high-volatility economies, SGL ranks better than both perfect foresight and Kalman filter learning. In low-volatility economies, perfect foresight has the better ranking, but the differences from the learning mechanisms are insignificant. In high-volatility economies, agents do better by not using the entire available time series for forming expectations. In low-volatility economies, the learning processes is not very different from the full information rational expectations approach.

Given that SGL performs better than the other mechanisms for the volatile economies, and that it performs almost as well as perfect foresight for the stable economies, we choose this tractable algorithm to construct series of GDP growth expectations for all the countries of our sample, since the end of the second world war. We compute interannual GDP growth forecasts (for example, for $t = 1950$, $E_t g_{t+1}^y$ is the expected growth rate of GDP in year 1950 for year 1951).

Stability of Expectations

After building series of GDP growth expectations, we compute series of stability of expectations between crisis($i - 1$) and crisis(i), which we denote by $SOE(i)$, for every country. As explained in section 2, $SOE(i)$ is the average of the sum of changes in expectations in between those crises:

$$SOE(i) = \frac{1}{t(i) - t(i-1)} \sum_{t=t(i-1)}^{t(i)} CE_{t-1,t} \quad (15)$$

where $t(i)$ is the year in which crisis i occurs.

Therefore, every period between two crises is associated with a different value of stability of expectations. A smaller value of $SOE(i)$ indicates that GDP growth expectations in between crisis $i - 1$ and i are less volatile.

4 Empirical analysis

Our analysis of the relationship between severity of crises and stability of expectations focuses separately on different types of financial crises.

Our first set of regressions focuses only on systemic banking crises and sovereign debt crises. These are the crises that involve massive defaults, either in the private sector or the public sector. Our second set of regressions adds inflation and currency crises to the above set. Hence, we use all the types of financial crises. Finally, our third set of regressions includes only inflation and currency crises.

We firstly estimate the following model with pooled data:

$$Sev_i = \alpha + \beta SOE_i + \gamma X_i + \epsilon_i \quad (16)$$

where X is the set of controls. If more stable expectations are associated to more severe crises, β should be negative.

Secondly, we use the panel to estimate the model with the inclusion of country-fixed effects. The fixed-effects control for time-invariant differences across countries, at the cost of removing much of the institutional and political variance in the data due to the infrequent occurrence of crises.

4.1 Results

Tables 2 to 8 show our preliminary results. Tables 2 to 7 use data on crises from Reinhart and Rogoff (2009). Table 8 uses data from Laeven and Valencia (2012). Columns 2 to 5 show the coefficients for the estimations using the four different measures of severity. Column 2 is the measure of severity calculating output growth losses according to the IMF methodology, using a five-years trend for output growth. Column 3 assigns the Reinhart and Rogoff (tables 2 to 7) or Laeven and Valencia (table 8) ending date of crises. Column 4 measures severity as the change in GDP between the year before and after the crisis. Column 5 measures severity as the change between the GDP trend observed the year before the crisis (using a five-years window) and GDP the year after the crisis.

Table 2 reports the results with the inclusion of only banking and debt crises, for the pooled data analysis (42 countries, 100 episodes of crises with measures of severity of columns 3 to 5, only 61 with IMF measure because the severity for those crises in which the GDP growth does not fall below the previous trend in any period after the crisis is not computed). The coefficient on stability of expectations is positive but not statistically significant for the measure of severity

that uses the IMF methodology, but it is negative and significant for the other three measures. The first measure overstates the output losses by more in stable countries. Countries with low volatility, after experiencing a crisis, still keep displaying low volatility of output. It is typical in those countries to move to a lower GDP growth trend after the crisis. With this methodology, in such situations the crisis would last for a very long time, even if the problems that generated it were already resolved. On the other hand, in highly volatile countries, it is statistically more likely to observe earlier after the crisis a GDP growth rate that it is above the pre-crisis trend.⁵ The other three measures produce results that conform to Minsky's FIH, i.e., more stable expectations are associated to more severe crises. Regressions reported in table 3 include fixed effects, and they display the same pattern of results.

In the regressions reported in tables 4 (pooled data) and 5 (panel data with country fixed effects), we add inflation and currency crises to the set of crises (42 countries, 221 episodes of crises with measures of severity of columns 3 to 5, only 129 with the IMF measure). The coefficients become statistically insignificant, except for the first measure of severity that displays a positive and significant coefficient. This apparent non-result is an important result. Inflation and currency crises are associated with extensive use of seigniorage. In those countries that exhibit a higher volatility of expectations, governments either face a higher cost for borrowing or are unable to borrow, resorting more to seigniorage. Hence, a higher volatility of expectations should lead to more severe inflation and currency crises, which implies a decrease in the coefficient of *SOE* when we include all the financial crises together, and a loss of their significance.

In this respect, table 6 shows that inflation and currency crises are indeed more severe when the instability of expectations is greater. These results do not hold with the inclusion of fixed effects (table 7).

The predictive power of the model, summarized in the values of R^2 , is always greater with the inclusion of country fixed-effects, what suggests that they are an important determinant of the severity of crises.

In the vicinity of a crisis, expectations may turn more volatile to the increased levels of uncertainty in the economy. This may lead to reversed causality: the

⁵Not surprisingly, this measure of severity is the least correlated with the other three measures.

expectation that a severe crisis is coming might affect the volatility expectations. To address this issue, we regress Sev_i in SOE_{i-x} , for $x = 1, 2, 3$. The patterns of results remain the same.

Finally, we report in table 8 the results of regressions including a set of controls. Due to data availability, we use a sample of 55 emerging and advanced economies for the period 1970-2012. We count 156 episodes of crises with measures of severity of columns 3 to 5, and only 87 with IMF measure. We include terms of trade, the log of GDP expressed in PPP terms, a measure of openness to trade, and interaction terms, all variables highlighted in the literature as important determinants of the severity of financial crises. A potential concern would be that the severity of crises is determined by those variables, and that those variables might be related to our measure of stability of expectations. We use Laeven and Valencia database, and we report the results only for banking and debt crises. The pattern of results still remains.

5 Conclusion

Our results suggest that the severity of overborrowing crises is negatively related to the volatility of GDP growth expectations. The theory behind this result is that a lower dispersion of forecasts, or equivalently, a higher degree of confidence in forecasts, leads to more borrowing and lending. Hence, when a crisis comes, the greater magnitude of the disruption of financial contracts translates into higher losses in the real sector, in terms of output growth.

On the other hand, a higher volatility of expectations, by making governments' borrowing more expensive, leads to a higher use of seigniorage and to more severe inflation and currency crises.

Appendix

Table 1: Correlations among measures of severity of crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
IMF	1			
RR dating	0.2549	1		
Δ GDP	0.2147	0.3712	1	
Δ (HP_GDP)	0.3048	0.4059	0.8813	1

Table 2: Pooled data, only banking and debt crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
SOE	53.421 (1.60)	-43.115 (2.35)**	-17.137 (2.72)***	-16.692 (3.61)***
Constant	0.131 (3.54)***	0.117 (4.91)***	0.042 (4.44)***	0.045 (5.54)***
Observations	61	100	100	100
R-squared	0.020	0.050	0.050	0.070

Table 3: Panel data, with fixed effects, only banking and debt crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
SOE	-1.762 (0.03)	-94.002 (3.25)***	-32.855 (3.03)***	-32.831 (3.47)***
Constant	0.195 (2.26)**	0.184 (4.19)***	0.063 (4.03)***	0.066 (4.36)***
Observations	61	100	100	100
R-squared	0.780	0.370	0.440	0.430

Table 4: Pooled data, all financial crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
SOE	141.147 (2.02)**	-21.748 (1.48)	4.358 (0.89)	1.989 (0.53)
Constant	0.030 (0.48)	0.069 (3.95)***	0.012 (1.95)*	0.015 (2.97)***
Observations	129	221	221	221
R-squared	0.080	0.020	0.010	0.000

Table 5: Panel data, with fixed effects, all financial crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
SOE	127.816 (1.30)	-57.548 (2.59)**	-3.180 (0.45)	-5.731 (1.07)
Constant	0.045 (0.43)	0.113 (4.03)***	0.021 (2.33)**	0.024 (3.33)***
Observations	129	221	221	221
R-squared	0.320	0.210	0.200	0.140

Table 6: Pooled data, only currency and inflation crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
SOE	175.051 (2.05)**	-2.582 (0.36)	9.787 (2.13)**	6.255 (1.71)*
Constant	-0.030 (0.40)	0.032 (3.25)***	0.003 (0.58)	0.005 (1.09)
Observations	87	156	156	156
R-squared	0.110	0.000	0.040	0.020

Table 7: Panel data, with fixed effects, only currency and inflation crises

	IMF	RR dating	Δ GDP	Δ (HP_GDP)
Stability of Expectations	181.225 (1.50)	-14.194 (1.04)	8.783 (1.14)	1.928 (0.33)
Constant	-0.037 (0.25)	0.047 (2.62)***	0.005 (0.45)	0.010 (1.32)
Observations	87	156	156	156
R-squared	0.430	0.190	0.250	0.190

Notes for Tables 2 to 7:

Absolute value of t-statistics in parentheses (Robust VCE estimation).

* significant at 10%; ** significant at 5%; *** significant at 1%

Dependent variable is Severity of Crises measured by:

IMF: Severity measured using IMF methodology.

RR dating: Severity measured using Reinhart and Rogoff (2009) crisis' end date.

Δ GDP: Severity measured as GDP change between the year before and after the crisis.

Δ (HP_GDP): Severity measured as change in GDP Hodrick-Prescott trend calculated the year before crisis and GDP of the year after crisis.

Table 8: Pooled data, only banking and debt crises, with controls (emerging and advanced economies)

	IMF	LV dating	Δ GDP	Δ (HP_GDP)
SOE	-37.356 (1.27)	-39.092 (3.02)***	-7.875 (1.27)	-21.210 (2.46)**
ToT (Terms of Trade)	-0.018 (0.70)	-0.016 (0.69)	-0.013 (1.14)	-0.005 (0.69)
Gross Domestic Product at PPP 2005	-0.289 (0.86)	-0.187 (0.75)	-0.115 (0.96)	-0.039 (0.53)
Openness ((X+M)/GDP)	0.094 (0.12)	0.307 (0.88)	0.025 (0.12)	-0.001 (0.01)
ToT * GDP	0.002 (0.67)	0.002 (0.72)	0.001 (1.05)	0.000 (0.61)
ToT * Openness	0.000 (0.03)	-0.002 (0.66)	0.000 (0.04)	0.000 (0.18)
Constant	2.794 (0.96)	1.681 (0.77)	1.125 (1.08)	0.453 (0.69)
Observations	57	83	83	83
R-squared	0.060	0.099	0.216	0.205

Notes:

Absolute value of t-statistics in parentheses (Robust VCE estimation).

* significant at 10%; ** significant at 5%; *** significant at 1%

Dependent variable is Severity of Crises measured by:

IMF: Severity measured using IMF methodology.

LV dating: Severity measured using Laeven and Valencia (2012) crisis' end date.

Δ GDP: Severity measured as GDP change between the year before and after the crisis.

Δ (HP_GDP): Severity measured as change in GDP Hodrick-Prescott trend calculated the year before crisis and GDP of the year after crisis.

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