Understanding the Relationship between GDP growth Expectations and Financial Crises*

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DRAFT
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Abstract

This paper explores two dimensions of the relationship between GDP growth expectations and financial crises. The first dimension is the relationship between volatility of GDP growth expectations and the frequency of financial crises. I describe the necessity of a high variance of expected permanent income to explain the frequency of crises we observe in highly volatile economies, and I show how models with learning about GDP growth trends are able to generate that high variance. The second dimension is the relationship between volatility of GDP growth expectations and the severity of financial crises, measured by output losses. I show that more stability of expectations is associated to more severe debt and banking crises, consistent with the Minsky financial instability hypothesis. Hence, more volatile countries have a higher probability of crisis, but a crisis tends to be more severe when it is preceded by long periods of stability.

Keywords: Expectations, Volatility, Financial Crises

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1 Introduction

Expectations are central for borrowing and lending decisions. Perceptions of higher future income lead to more borrowing and lending in the present. The validation of those expectations is central for financial instability. When realizations of income are significantly lower than previous expectations, promises may not be consistent with the satisfaction of credit constraints. Sovereign default and banking crises are characterized by scenarios of large-scale broken promises.

Large discrepancies between expectations on and realizations of permanent income are a more recurrent phenomenon in emerging economies than in developed economies. Consistently, the frequency of debt and banking crises is high in emerging economies but low in developed economies.

Reinhart and Rogoff (2009) document that debt and banking crises are preceded by rapid rises in asset prices followed by crashes. The standard interpretation of these asset price crashes is that they reflect large downward revisions of expected permanent income. In any model featuring stochastic output and trend shocks, these events occur with positive probability. The first issue that this paper investigates is what kind of processes for formation of expectations on permanent income can produce the sufficiently large variance that is needed to explain the high frequency of crises in emerging economies. Specifically, are models that assume full information rational expectations able to capture the high variance of expected permanent income, hence the high frequency of crises observed in emerging economies? The answer is negative. The full information rational expectations (FIRE) benchmark produces a variance and persistence of permanent shocks to output that it is too low to replicate the high variance of expected permanent income needed for a high frequency of crises.¹

Deviating from the FIRE benchmark in ways that allow for incorporation of learning mechanisms improve the capacity of explaining the actual frequency of crises. The reason is that learning mechanisms increase the perceived variance of expected permanent income with respect to the FIRE benchmark, and the increase is comparatively higher in the more volatile economies. Therefore, models with

¹This low variance of permanent shocks also implies that the model with full information rational expectations does not do a good job at explaining business cycles in emerging economies (Garcia Cicco, Pancrazzi, and Uribe (2010)).
learning for formation of expectations improve the match between theoretical and actual frequency of crises by comparatively more in emerging economies than in developed economies. This is the topic of section 2 of the paper.

The second dimension of analysis of this paper centers on the relationship between expectations of future income and the severity of financial crises. We analyze 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. This topic is developed in section 3.

These pervasive effects of volatility on financial crises frequency and severity call for macro policies. Section 4 analyzes the type of policies that may mitigate the problems of high frequency and high severity of crises, taking up the insights from the literature on subjective expectations (Weitzman (2007)) and from the literature on macroeconomic externalities and macroprudential policies (Korinek (2010, 2011), Jeanne and Korinek (2010)).

1.1 Literature review

Recent literature has taken up the point that volatility of growth trends is an important factor for explaining business cycles in emerging economies (Aguiar and Gopinath (2007), although with important caveats pointed out in Garcia-Cicco et al (2010)). An extension of that branch of the literature has also shown how models with learning can better produce the levels of growth trends that are consistent with the evidence for emerging economies (Boz et al (2011)).

The role of wealth misperceptions and broken promises for explaining financial crises in emerging economies, with special emphasis in Argentina, has been analyzed by Heymann and Sanguinetti (1998), Galiani, Heymann, and Tommasi (2003), Heymann (2009). The mechanism of intertemporal failures of coordination
has old roots in Keynes (1937), Clower and Leijonhufvud (1975), and Leijonhufvud (1981), among other important contributions.

The analysis of the relationship between volatility of expectations and severity of crises 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.

2 Volatility of expectations and frequency of crises

Emerging economies exhibit a higher frequency of banking and sovereign debt crises than developed economies. Any model that attempts to explain this fact must generate a variance of expected permanent income that is sufficiently larger in emerging economies. This section explains how learning mechanisms for formation of expectations amplify the effects of output growth volatility on the volatility of expectations, being able to capture better the phenomena of large swings in expected permanent income than models that, by definition, make learning irrelevant.

2.1 A baseline model of default

This section presents a model of strategic default that I will use as a benchmark to show the importance of beliefs on type of shocks and expectations about future
output for matching frequency of crises. The basic framework is introduced in Eaton and Gersovitz (1981) and Aguiar and Gopinath (2006).

The model features an small and open economy of a representative agent that receives an exogenous and stochastic stream of output. Output is composed of a transitory component $z_t$ and a trend component $\Gamma_t$:

$$Y_t = e^{z_t} \Gamma_t$$

with $\Gamma_t = e^{g_t} \Gamma_{t-1}$

The aggregate growth shock can be decomposed into a permanent and a transitory component:

$$g_t^y = \ln \left( \frac{Y_t}{Y_{t-1}} \right) = g_t + z_t - z_{t-1}$$

The transitory shocks $z_t$ follow an AR(1) process:

$$z_t = \rho_z z_{t-1} + \epsilon_t^z$$

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

Cumulative permanent shocks $g_t$ are described by

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

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

There is a single international asset $d_{t+1}$ (defined as "debt") with one period of maturity. The agent receives $q$ units of the good in this period in exchange of a promise of returning one unit of the good in the next period.

There is a single good. The utility defined over that good is of a CRRA type:

$$u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$$

The present value of utility (value function) at time $t$ depends on the amount
the agent borrowed, and on the perception she has about the type of shocks the economy received in that period: \( V(d_t, \tilde{z}_t, \tilde{g}_t) \), where \( \tilde{z}_t \) and \( \tilde{g}_t \) are the beliefs about the transitory and permanent shocks, respectively.

In every period, the agent decides whether she pays the debt or defaults. There is no possibility of partial default. If she pays, she is in “good standing” and her “value function” is \( V^G \). If she defaults, she is in “bad standing” and her “value function” is \( V^B \). The value function in each period is the maximum between \( V^G \) and \( V^B \): 
\[
V(d_t, \tilde{z}_t, \tilde{g}_t) = \max\{V^G(d_t, \tilde{z}_t, \tilde{g}_t), V^B(\tilde{z}_t, \tilde{g}_t)\}.
\]

If the agent does not default on her debt, she has access to the credit market at time \( t \). She chooses consumption optimally subject to her budget constraint. She initiates period \( t+1 \) with an stock of assets \( d_{t+1} \). Therefore, the value function of being in good standing is given by
\[
V^G(d_t, \tilde{z}_t, \tilde{g}_t) = \max\{c_t\} \{u(c_t) + \beta E_t V(d_{t+1}, \tilde{z}_{t+1}, \tilde{g}_{t+1})\} \tag{6}
\]
subject to
\[
c_t = y_t - d_t + q_tD_{t+1} \tag{7}
\]
where \( \beta \) is the discount factor and \( E_t \) is the expectation at time \( t \) over next period’s output shocks.

If the agent defaults on her debt, she is in autarky. Hence, at time \( t \) she can only consume the endowment \( y_t \) net of a fraction \( \delta \) that is lost due to defaulting. With probability \( \lambda \) she is redeemed, i.e. she can have access to the credit market again and she has to repay no debt. With probability \( 1 - \lambda \) she remains in autarky at time \( t+1 \). Therefore, the value function of being in bad standing is given by
\[
V^B(\tilde{z}_t, \tilde{g}_t) = u[(1 - \delta)y_t] + \beta[\lambda E_t V(0, \tilde{z}_{t+1}, \tilde{g}_{t+1}) + (1 - \lambda)E_t V^B(\tilde{z}_{t+1}, \tilde{g}_{t+1})] \tag{8}
\]

The default function is given by
\[
D(d_t, z_t, g_t) = 1 \text{ if } V^B(z_t, g_t) > V^G(d_t, z_t, g_t) \tag{9}
\]
and zero otherwise.

The capital market is composed of risk-neutral international investors whose opportunity cost is the risk-free interest rate \( r^* \). Then, the equilibrium condition
in the capital market must satisfy

\[ q(d_{t+1}, z_t, g_t) = \frac{E_t(1 - D_{t+1})}{1 + r^*} \]  \hspace{1cm} (10)

2.2 The role of beliefs

Borrowing decisions will be determined by the interpretation that the agent makes about the decomposition of the aggregate shocks that the economy receives.

2.2.1 Full information rational expectations

Full information in this context means that the agent can perfectly identify whether a shock to output is permanent (\(g\)-type) or transitory (\(z\)-type). For every state for every shock, the agent knows the probability of transiting to another state, \(Pr(z_{t+1} = z_i/z_t = z_j)\) and \(Pr(g_{t+1} = g_i/g_t = g_j)\).

Previous literature shows that when the parameters that govern the productivity processes are estimated by using the long time-series methodology, the variance of the persistence of the permanent shocks is not large enough to allow the FIRE benchmark for matching satisfactorily the empirical frequency of overborrowing crises in emerging economies (see Garcia Cicco et al (2010), Guzman (2013)).

2.2.2 Is FIRE a good approximation to survey data on expectations

How good is the assumption of FIRE as an approximation for actual expectations? To answer this question, I use survey data on expectations. The Survey of Professional Forecasters (SPF) of Consensus Forecasts provides quarterly data on inter-annual GDP growth expectations since 1999 for several developed and emerging economies.

Let \(g_t^y\) be the growth rate of output at time \(t\). If the agent has FIRE, we should observe

\[ g_{t+1}^y = E_t g_{t+1}^y + \epsilon_{t+1} \]  \hspace{1cm} (11)

with

\[ E(\epsilon_{t+1}) = 0 \ \& \ E(\epsilon_t \cdot \epsilon_{t+1}) = 0 \ \forall t > 0 \]  \hspace{1cm} (12)

That is, the actual growth rate of output should be equal to the expected growth.
rate plus a forecast error that should have a sample mean equal to zero and should have no serial autocorrelation under the null of FIRE.

If we test the conditions on the forecast errors on GDP growth expectations under the null of FIRE for the sample available in the SPF, we obtain the following facts:

1. The sample mean of forecast errors is not significantly different from zero in any of the developed countries of the sample. It significantly differs from zero for a few emerging economies.

2. First order autocorrelations of forecast errors are positive and significant in some emerging economies, while there is no developed economy for which this also holds. The interpretation of this result for the emerging economies is that if the current GDP growth forecast is above (below) the actual realization, next period growth will probably be overestimated (underestimated) again.

As emphasized by Mankiw et al (2004), the assumption of FIRE is easy to disprove. The fact that economic agents systematically disagree about expected outcomes is inherently inconsistent with all agents knowing the true structure of the model and perfectly observing all economic variables and shocks in real-time. What matters for economic analysis is not whether the assumption is literally true, since it is clearly not, but rather whether deviations from FIRE are significant enough to have important economic implications. With this short sample, we cannot tell whether these deviations from FIRE come from the FI side or the RE side. However, a sensible first step is to analyze the consequences of getting rid of the assumption of full information while maintaining the assumption of rational expectations for formation of beliefs on output shocks. A sensible second step is to analyze the consequences of getting rid of the assumption of rational expectations by exploring a non-Bayesian learning mechanism, whose predicted expectations match the survey data on expectations even better than expectations based on Bayesian learning. Guzman (2013) does both. By exploring these alternative learning mechanisms, we can assess the economic significance of deviations from FIRE for explaining debt crises.
2.2.3 The comparatively different nature of learning across economies with different volatility

The process of formation of expectations presents different difficulties for economies with different characteristics. The above described evidence from survey data shows that professional forecasters make bigger errors in emerging economies than in developed economies, and that processing information optimally is also a more difficult task in the former economies.

Figures 1 and 2 show the recursive GDP per capita Hodrick-Prescott trends for one developed economy (United States) and one emerging economy (Argentina) to intuitively illustrate how the processes of identification of output trends can differ among economies with different levels of volatility. The trends are calculated by extending the time-window, setting the origin in 1970, with annual data from the World Development Indicators of the World Bank.

In United States, when I extend the time-series, every trend looks as an extension of the previous one (the new trend lies on the former trend). For the agent living in this economy, the past seems an accurate source of information for identifying future GDP per capita trends. If the American agent was trying to learn about the behavior of GDP per capita trends by using information from the past, the length of the relevant time-series would increase through time.

In Argentina, the behavior of recursive trends is drastically different. Every time I extend the time-series, the trend changes. For the agent living in this economy, the past does not seem to be an accurate source of information for identifying future GDP per capita trends. Indeed, if the agent tried to learn about the output trends in the aftermath of structural breaks by using data prior to those breaks, predictions would be too different from realizations. The relevant time-series for learning about future trends are shorter than in the case of the United States, suggesting that the learning process is more difficult and more volatile in Argentina than in the United States.

The learning mechanisms described in this paper capture this intuition.
Figure 1: Recursive GDP per capita trends, United States
Figure 2: Recursive GDP per capita trends, Argentina
2.2.4 Bayesian learning

Bayesian learning assumes that the agent is imperfectly informed about the nature of shocks the economy receives. The agent rationally process the signals that receives. These signals are the aggregate growth shocks that hit the economy. This is the rational expectations approach in a context of imperfect information on the nature of shocks, in which the agent uses the Kalman filter in order to update beliefs.

To describe the filtering problem analytically, I express it in matrix form:

\[ g_t^Y = \ln\left(\frac{Y_t}{Y_{t-1}}\right) = \begin{bmatrix} 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} z_t \\ z_{t-1} \\ g_t \end{bmatrix} \] \tag{13}

with

\[
\begin{bmatrix} z_t \\ z_{t-1} \\ g_t \end{bmatrix} = \begin{bmatrix} \rho_z & 0 & 0 \\ 1 & 0 & 0 \\ 0 & \rho_g & 0 \end{bmatrix} \begin{bmatrix} z_{t-1} \\ z_{t-2} \\ g_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ (1 - \rho_g) \mu_g \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^z \\ \epsilon_t^g \end{bmatrix} \] \tag{14}

Define the following notation:

\[ Z = \begin{bmatrix} 1 & -1 & 1 \end{bmatrix}; \alpha_t = \begin{bmatrix} z_t \\ z_{t-1} \\ g_t \end{bmatrix}; T = \begin{bmatrix} \rho_z & 0 & 0 \\ 1 & 0 & 0 \\ 0 & \rho_g & 0 \end{bmatrix} \]

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

\[ \eta_t \sim N(0, Q); Q = \begin{bmatrix} \sigma^2_z & 0 \\ 0 & \sigma^2_g \end{bmatrix} \]

The goal is to estimate \( \alpha_t = \begin{bmatrix} z_t & z_{t-1} & g_t \end{bmatrix}' \) optimally. Given normality of errors, the optimal estimator \( a_t = E(\alpha_t/I_t) \) is linear.

The Kalman coefficients are the parameters \( k_1 \) and \( k_2 \) of an adaptive rule for the posterior \( a_t \) that is a linear combination of prior beliefs \( a_{t/t-1} \) and the new
signal \( g^Y_t \):

\[
a_t = k_1 a_{t/t-1} + k_2 g^Y_t
\]  

(15)

where

\[
k_1 = I - PZ'(ZPZ')^{-1}Z
\]  

(16)

\[
k_2 = PZ'(ZPZ')^{-1}
\]  

(17)

and

\[
a_{t/t-1} = Ta_{t-1} + c
\]  

(18)

\( P \) 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:

\[
P = TPT' - TPZ'(ZPZ')^{-1}ZPT' + RQR'
\]  

(19)

\( a_t = \begin{bmatrix} \tilde{z}_t & \tilde{z}_{t-1} & \tilde{g}_t \end{bmatrix}' \) is the vector of the beliefs used in the value functions \( V^G \) and \( V^B \). The Kalman coefficients used for updating these beliefs are such that the larger the relative variability of permanent shocks, the larger the share of growth changes attributed to the permanent component.

**Frequency of crises under Bayesian learning**  To understand how this type of learning affects the probability of a debt or banking crisis, we first need to understand how every type of shock affects that probability. This task must be assessed by performing a comparison of the changes of the value functions associated with each state when the economy receives either a transitory or a permanent shock. Formally, we need to compare \( |\frac{\partial V_G}{\partial z_t} - \frac{\partial V_B}{\partial z_t}| \) with \( |\frac{\partial V_G}{\partial g_t} - \frac{\partial V_B}{\partial g_t}| \).

How big is \( |\frac{\partial V_G}{\partial z_t} - \frac{\partial V_B}{\partial z_t}| \)? A “small” number. To see why, firstly suppose \( z_t \)-shocks are purely iid (\( \rho_z = 0 \)). Then, the agent has a motive for saving but the impact of a shock on her present value of output is small. Hence, the impact on her present value of utility, either if she is in good standing (\( V^G \)) or if she is in bad standing (\( V^B \)), is also small, which implies that the above difference is small. On the other extreme, suppose \( z_t \) follows a random walk (\( \rho_z = 1 \)). Then, even though the effect of a shock on the agent’s present value of output would be bigger, there would be limited need to save out of additional income. Hence, the value of financial integration would also be small.
How big is $|\frac{\partial V^C}{\partial g_t} - \frac{\partial V^B}{\partial g_t}|$? When there is a shock to the trend, the agent knows that output will be permanently affected. A positive shock generates large incentives to borrow today, while a negative shock generates large incentives to save today. In general, with permanent cumulative shocks, the value of financial integration is greater than with transitory shocks.

Learning increases the probability of a crisis because it increases the variance of beliefs about permanent shocks with respect to the FIRE benchmark. There are two reasons for this effect. The first reason is the fact that with imperfect information there is an additional layer of uncertainty about permanent income: When the agent form beliefs about the decomposition of the aggregate shocks, unlike with FIRE, those beliefs are not necessarily correct, what can lead to further revisions that increase the size of the perceived permanent shocks. This mechanism has been pointed out in Boz et al (2011). To describe it analytically, consider the decomposition of the growth rate of output. Under FIRE, the decomposition is given by

$$g^y_t = \ln \left( \frac{Y_t}{Y_{t-1}} \right) = z_t - z_{t-1} + g_t$$

Under Bayesian learning, the decomposition is given by

$$g^y_t = \ln \left( \frac{\tilde{Y}_t}{\tilde{Y}_{t-1}} \right) = \tilde{z}_t - \tilde{z}_{t-1} + \tilde{g}_t$$

Under FIRE, when the economy receives an aggregate growth shock, previous beliefs are not updated (they were always correct). Under Bayesian learning, instead, when the economy is hit by an aggregate growth shock the agent can update their beliefs on three components: the contemporaneous permanent component $\tilde{g}_t$, the contemporaneous cyclical component $\tilde{z}_t$, or the previous period’s cyclical component $\tilde{z}_{t-1}$. When the agent revises her previous belief on the cyclical shocks, she is revising the contemporaneous belief on the permanent shock. Suppose that the economy received a negative aggregate growth shock in the past and the agent attributed it to the cyclical component. If in the present she revises her previous beliefs by thinking that the shock was permanent instead of transitory, that revision will be incorporated on the belief about the contemporaneous permanent shock by having a lower value than otherwise would have had.
For an illustration of this mechanism, let’s consider the following example. In Argentina, the annual rates of output growth, $g^p_t$, from 1998 to 2000, were the following: $g^p_{1999} = -0.03$ and $g^p_{2000} = -0.01$. Let $g_t$ and $z_t$ denote the beliefs about the permanent and transitory component of the aggregate shock $g^p_t$, respectively. Suppose, without loss of generality, that the entire decrease in output was due to permanent shocks. Consider two alternative evolutions of beliefs. In the first case, the agent interprets every aggregate shock as a permanent shock. Hence, her set of beliefs is \{\(z_{1999}, z_{2000}\)\} = \{0, 0\} and \{\(g_{1999}, g_{2000}\)\} = \{-0.03, -0.01\}. In the second case, the agent starts thinking in 1999 that the aggregate growth shock is completely transitory (i.e., $z_{1999} = -0.03$ and $g_{1999} = 0$), but in 2000 she revises her beliefs on the previous cyclical shock, recognizing that the previous aggregate shock was permanent. Then, in 2000 she will believe $z_{1999} = 0$ instead of $z_{1999} = -0.03$, an upward revision of 3 percentage points, which will imply a belief $g_{2000} = -0.04$ instead of $g_{2000} = -0.01$, increasing the size of the perceived permanent shock. The variance of this stream of beliefs \{\(g_{1999}, g_{2000}\)\} = \{0, -0.04\} is greater than the variance of the previous beliefs \{\(g_{1999}, g_{2000}\)\} = \{-0.03, -0.01\}.

The second reason comes from the fact that the share of the aggregate shock attributed to the permanent component is increasing in the variance of permanent shocks.

### 2.2.5 Stochastic-gain learning (SGL)

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

\[
E_tg_{t+1}^y = E_{t-1}g_t^y + \kappa_t(g_t^y - E_{t-1}g_t^y)
\]  

(20)

with

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

(21)

where \( \kappa_t \) 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 \( \frac{1}{\kappa_t + 1} \), 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 1** Asymptotic rationality (AR): \( p^{\epsilon,T} \) converges to 1 for \( T \) large, \( \forall \epsilon > 0 \)

**Definition 2** Epsilon-Delta Rationality (EDR): for \( (\epsilon, \delta, T) \), \( p^{\epsilon,T} \geq 1 - \delta \), for \( \delta > 0 \)

**Definition 3** Internal consistency (IC): After \( T \) periods, the average perceived error using the rule for \( \kappa_t \) is smaller than under any alternative learning rule for \( \kappa_t \) (studied only for “moderately high” \( T \))

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

**Frequency of crises under Stochastic-gain learning** SGL increases the likelihood of a crisis by increasing the variance of expected permanent income. The increase in the variance of expected permanent income with SGL with respect
to the FIRE benchmark is large for emerging economies but it is not large for developed economies. There are two mechanisms that imply this result.

The first mechanism is related to the size of forecast errors. In economies with a larger variance of the permanent component of the aggregate shock, the average size of forecast errors is larger, adding more variance to expected growth rates of output. Figure 3 shows two different paths of expectations under SGL: one path occurs when there are only permanent shocks, and the other occurs when there are only transitory shocks, such that the variance of output is the same for every path. We observe that expectations on output growth are more volatile when there are only permanent shocks than when there are only transitory shocks.

The second mechanism is related to the coefficient that determines how sensitive expectations are with respect to forecast errors, i.e., the gain parameter. This parameter is decreasing when errors are small and constant when errors are large. In a country like Canada, in which the growth rate of output exhibits low volatility, forecast errors tend to be small during long periods. Hence, the gain parameter decreases along time, implying small updates in expectations. On the other hand, in a country like Argentina, forecast errors are often sufficiently large to lead agents to use a constant gain parameter. Then, the average size of the gain parameter is larger for Argentina than for Canada, implying larger revisions of expectations in the former country. Besides, quantitatively, the variance of expected permanent income for emerging economies is also larger than the one implied by Bayesian Kalman filter learning. As a result, the increase in the frequencies of crises for emerging economies with respect to FIRE is higher with SGL than with Bayesian Kalman filter learning.

### 3 Volatility of expectations and severity of crises

In this section we turn the attention to a different dimension of the relationship between expectations and financial crises. Minsky’s Financial Instability Hypothesis (FIH) establishes that a crisis tends to be more probable and more severe the longer the last crisis recedes into the past. This hypothesis has been described as “stability leading to instability”. We specifically explore whether more stability of expectations is associated with more severe financial crises.
Figure 3: Output growth expectations with SGL
3.1 GDP growth 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.\textsuperscript{2}

The SPF offers quarterly data on GDP growth expectations since 1999. We calculate the average sum of squared differences between actual expectations and theoretical 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,\textsuperscript{2}

\textsuperscript{2}In the calculations that we perform, we assign the perfect information model parameters to the imperfect information rational expectations mechanism, as in Guzman (2013).
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 \( t = 1950 \), \( E_{tg_{t+1}} \) is the expected growth rate of GDP in year 1950 for year 1951).

3.2 Stability of Expectations

After building series of GDP growth expectations, we compute series of stability of expectations between crisis \((i - 1)\) and crisis \(i\). For that purpose, we define the two following concepts:

**Definition 4 – Change in expectations.** \( CE_{t-1,t} \) is the change in output growth expectations from period \( t - 1 \) to \( t \),

\[
CE_{t-1,t} = |E_{tg_{t+1}} - E_{t-1g_{t}}|
\]

**Definition 5 – Stability of expectations.** \( SOE(i) \) is a measure of the stability of expectations between crisis \(i - 1\) and \(i\):

\[
SOE(i) = \frac{1}{t(i) - t(i - 1)} \sum_{t=t(i-1)}^{t(i)} CE_{t-1,t}
\]

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.
3.3 Measuring severity

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.

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

$$Sev(t_0) = \sum_{t=t_0}^{t_n} (\tilde{g}_{t_0}^y - g_t^y)$$  \hspace{1cm} (22)

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 $t$.

We use the crises panel datasets from Reinhart and Rogoff (2009) on four types of financial crises: banking, sovereign debt, inflation, and currency crises.

Our first measure of severity follows the IMF (1998)’s methodology. 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 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 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 Reinhart and Rogoff (2009) 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 more the overestimation of output growth loss.

3.4 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:

\[ Sev_i = \alpha + \beta SOE_i + \gamma X_i + \epsilon_i \]  

(23)

where \( X \) is the set of controls. If more stable expectations are associated to more severe crises, \( \beta \) 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.

### 3.5 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.\(^3\) 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 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.

In summary, the severity of banking and debt crises is negatively related to the volatility of GDP growth expectations. On the other hand, a higher volatility of

\(^3\)Not surprisingly, this measure of severity is the least correlated with the other three measures.
expectations is associated with more severe inflation and currency crises

4 An analysis of policy implications

In this section I elaborate on extensions of the results obtained in the paper that are specifically referred to policy implications.

I have described how, in the absence of knowledge of the distribution of probabilities that determine productivity, the use of information from the past to update beliefs may increase macroeconomic volatility through two channels: increases in the probability of crises, and increases in their severity.

The initial volatility of shocks is accelerated by the learning process, leading to larger swings in expectations of permanent income, making identification of trends a more difficult process.

Misperceived trends may result in procyclical policies and financial crises. Suppose, for example, that a government wants to run a countercyclical fiscal policy. To succeed in the goal of being countercyclical, the government needs to determine the growth trend rate of the economy. If a government is ex-post overoptimistic, it may end up running an (undesired) procyclical fiscal policy, being too expansionary when it should have been more cautious. If it is ex-post overpesimistic, it also may end up running an (undesired) procyclical fiscal policy, being underexpansionary at the moment it should have spent more. A numerical example may serve to illustrate this phenomenon. Suppose that the growth rate today is 5%, and that the government believes that the growth trend rate will be 7%. Then, government runs an expansionary policy. If, however, the growth trend is revealed to be, say, 3%, that policy will be judged ex-post as procyclical. And viceversa.

Erring on either side will imply intertemporal consumption misallocations for the society. If the cost of erring on each side was symmetric, there would be no much to do. However, if the cost of erring on the too-expansionary side is greater than the one on the too-underexpansionary side (due to the fact that erring on the too-expansionary side may trigger a crisis), the existence of structural uncertainty would imply that fiscal policy should be more cautious than what a Ramsey framework with no structural uncertainty would imply. This argument has parallelisms with arguments of the climate change literature that establish
that, in the presence of structural uncertainty about the variance of shocks, the optimal behavior is more precautionary than if the only uncertainty is about the mean (Weitzman 2007, 2009). Note, also, that if a country would manage to decrease its level of growth trend volatility, it would need to save less –hence a precautionary fiscal policy that reduces variance of expected revenues could imply a need of a less precautionary fiscal policy in the future.

On the other hand, this paper has made the point that long periods of low volatility tend to generate overconfidence in own forecasts that may lead to excessive levels of leverage, such that if those forecasts happen to be incorrect in a magnitude that triggers a crisis, the crisis tends to be more severe. What can policy do to mitigate the effects of overconfidence in a learning environment on the severity of crises?

Macroprudential regulations that prevent excessive leverage would be measures that could address this concern. The theoretical literature on macroeconomic externalities in the processes of leverage and deleverage has made a convincing claim in this direction (Eggertsson and Krugman (2012), Howitt (2011), Korinek (2010, 2011), Jeanne and Korinek (2010)). The main problem with excessive leverage is excessive deleverage.

In summary, the two dimensions of the relationship between growth expectations and crises analyzed in this paper call for prudential policies on the macro side. The precise theoretical links between the results herein established and the potential policy implications elaborated will be the subject of other papers.

5 Conclusion

The identification of expected permanent income is a key determinant of crises that involve massive breaches of contracts, like sovereign debt and banking crises. Mechanisms that incorporate learning for formation of expectations have the capacity of generating levels of variance of expected permanent income that are compatible with the levels required to explain the frequency of that type of crises in emerging economies.

The severity of banking and debt 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.

These results call for macroeconomic policies that morigerate the excessive volatility of expectations, and that at the same time prevent excessive leverage when expectations become stable.
Appendix

**Table 1:** Correlations among measures of severity of crises

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP_GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMF</td>
<td>1</td>
<td>0.2549</td>
<td>0.2147</td>
<td>0.3048</td>
</tr>
<tr>
<td>RR dating</td>
<td>0.2549</td>
<td>1</td>
<td>0.3712</td>
<td>0.4059</td>
</tr>
<tr>
<td>ΔGDP</td>
<td>0.2147</td>
<td>0.3712</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Δ(HP_GDP)</td>
<td>0.3048</td>
<td>0.4059</td>
<td>0.8813</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 2:** Pooled data, only banking and debt crises

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP_GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOE</td>
<td>53.421</td>
<td>-43.115</td>
<td>-17.137</td>
<td>-16.692</td>
</tr>
<tr>
<td></td>
<td>(1.60)</td>
<td>(2.35)**</td>
<td>(2.72)**</td>
<td>(3.61)**</td>
</tr>
<tr>
<td>Constant</td>
<td>0.131</td>
<td>0.117</td>
<td>0.042</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(3.54)**</td>
<td>(4.91)**</td>
<td>(4.44)**</td>
<td>(5.54)**</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.020</td>
<td>0.050</td>
<td>0.050</td>
<td>0.070</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP_GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOE</td>
<td>-1.762</td>
<td>-94.002</td>
<td>-32.855</td>
<td>-32.831</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(3.25)**</td>
<td>(3.03)**</td>
<td>(3.47)**</td>
</tr>
<tr>
<td>Constant</td>
<td>0.195</td>
<td>0.184</td>
<td>0.063</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(2.26)**</td>
<td>(4.19)**</td>
<td>(4.03)**</td>
<td>(4.36)**</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.780</td>
<td>0.370</td>
<td>0.440</td>
<td>0.430</td>
</tr>
</tbody>
</table>
Table 4: Pooled data, all financial crises

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP.GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOE</td>
<td>141.147</td>
<td>-21.748</td>
<td>4.358</td>
<td>1.989</td>
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<tr>
<td></td>
<td>(2.02)**</td>
<td>(1.48)</td>
<td>(0.89)</td>
<td>(0.53)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.030</td>
<td>0.069</td>
<td>0.012</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(3.95)***</td>
<td>(1.95)*</td>
<td>(2.97)***</td>
</tr>
<tr>
<td>Observations</td>
<td>129</td>
<td>221</td>
<td>221</td>
<td>221</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.080</td>
<td>0.020</td>
<td>0.010</td>
<td>0.000</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP.GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOE</td>
<td>127.816</td>
<td>-57.548</td>
<td>-3.180</td>
<td>-5.731</td>
</tr>
<tr>
<td></td>
<td>(1.30)</td>
<td>(2.59)**</td>
<td>(0.45)</td>
<td>(1.07)</td>
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<td>Constant</td>
<td>0.045</td>
<td>0.113</td>
<td>0.021</td>
<td>0.024</td>
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<tr>
<td></td>
<td>(0.43)</td>
<td>(4.03)***</td>
<td>(2.33)**</td>
<td>(3.33)***</td>
</tr>
<tr>
<td>Observations</td>
<td>129</td>
<td>221</td>
<td>221</td>
<td>221</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.320</td>
<td>0.210</td>
<td>0.200</td>
<td>0.140</td>
</tr>
</tbody>
</table>

Table 6: Pooled data, only currency and inflation crises

<table>
<thead>
<tr>
<th></th>
<th>IMF</th>
<th>RR dating</th>
<th>ΔGDP</th>
<th>Δ(HP.GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOE</td>
<td>175.051</td>
<td>-2.582</td>
<td>9.787</td>
<td>6.255</td>
</tr>
<tr>
<td></td>
<td>(2.05)**</td>
<td>(0.36)</td>
<td>(2.13)**</td>
<td>(1.71)*</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.030</td>
<td>0.032</td>
<td>0.003</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(3.25)***</td>
<td>(0.58)</td>
<td>(1.09)</td>
</tr>
<tr>
<td>Observations</td>
<td>87</td>
<td>156</td>
<td>156</td>
<td>156</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.110</td>
<td>0.000</td>
<td>0.040</td>
<td>0.020</td>
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<tr>
<td></td>
<td>IMF</td>
<td>RR dating</td>
<td>∆GDP</td>
<td>∆(HP, GDP)</td>
</tr>
<tr>
<td>--------------------------</td>
<td>-------</td>
<td>-----------</td>
<td>------</td>
<td>-----------</td>
</tr>
<tr>
<td></td>
<td>(1.50)</td>
<td>(1.04)</td>
<td>(1.14)</td>
<td>(0.33)</td>
</tr>
<tr>
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<td>0.005</td>
<td>0.010</td>
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<td></td>
<td>(0.25)</td>
<td>(2.62)***</td>
<td>(0.45)</td>
<td>(1.32)</td>
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<tr>
<td>Observations</td>
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<td>156</td>
<td>156</td>
<td>156</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.430</td>
<td>0.190</td>
<td>0.250</td>
<td>0.190</td>
</tr>
</tbody>
</table>

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.
ΔGDP: 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.
References


