

UNDERSTANDING THE CAUSES AND EFFECTS OF FINANCIAL CRISES

BY

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Vita

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Preface

Writing this doctoral dissertation allowed me to address the topics that have captured my deepest curiosity and interest since my youth: Economic depressions and financial crises.

I was born in Argentina, the country with the highest frequency of financial crises during the last century. During my childhood, adolescence, and early stages of adulthood, I had a first-hand experience with turbulent economic times. I experienced the hyperinflation crisis of the late 1980s – with an annual inflation rate of 3,079.5 percent in 1989, and the poverty rate reaching what by the time was the historical record of 47.3 percent – and the huge economic depression of 1998-2002 that resulted in the most severe financial crisis in the history of the country – with the poverty rate reaching a new historical record of 57.5 percent, extreme poverty reaching a maximum of 27.5 percent in October of 2002, a rate of unemployment of 20.8 percent, a GDP drop of 11 percent in 2002, and the president escaping from the Government's House in December of 2001 in a helicopter, in the middle of intense and violent riots and clashes with the police that led to 39 deaths over the country. I discovered that economic crises are terrible events for societies, especially when they involve high unemployment and lack of opportunities.

The problems that concerned me with the crisis were not only economic in nature (like the underutilization of the resources of the society), but also social. Unemployment and decreasing real wages are transmitters of familial problems, like divorces, lack of attention towards children, lack of motivation of the young generations that find it difficult to access the economic system, and several other problems. The effects of these phenomena do not disappear when the crisis is solved. Instead, they may

persist for a long time.

Crises may destroy the working capabilities of the current and future generations. In a system with institutions that do not provide proper social safety nets, the children of the unemployed urban population will face tough conditions that may affect their behavior permanently: they will eat less, they will receive worse education (both formal and informal), they will have less access to health care, they will suffer more from exclusion, and they will tend to be less motivated. They are also more prone to be engaged in criminal activities, as academic research shows. The children of these children, if social safety nets are still underdeveloped by the time they are born, will most likely face the same problems.

The negative effects of deep economic depressions and crises are long-lasting. Economic policies should aim to prevent them and to manage them properly if they occur. In order to succeed in this task, we need to be able to answer some important questions: Why do these crises occur? What are their determinants? What are their consequences? Why do so many families experience such tremendous intertemporal consumption misallocations? These are the questions that motivate this dissertation. I intend to provide answers to some of their aspects in chapters 1 to 3.

Chapter 1 explores the role of a key element for the occurrence of crises that involve massive defaults: the identification of real income growth trends. The expectations of permanent income (an object that measures the purchasing capacity of an individual through her lifetime) are more volatile in unstable than in stable environments. This leads to large changes across time in the levels of consumption, and to more frequent situations where people find that the amount they borrowed is “too high” relative to their actual repayment capacity. The world nowadays abounds in situations where families lose a significant part of their wealth during times of crises (like losing one’s house, the most important asset of any middle-income family). Several European

countries are immersed in costly crises in which the citizens discover that their permanent income is lower than what they were expecting a few years before. Learning the levels of permanent income is not an easy task – definitely more difficult than what models of rational expectations would imply, especially in volatile economies. I show that models that incorporate learning for formation of expectations can better account for the variance of expected permanent income that is consistent with the frequency of crises we observe.

Chapter 2 analyzes the relationship between financial reforms and financial instability. I have been studying these issues with Pablo Gluzmann, an exceptional doctoral student from Universidad Nacional de La Plata. During the 1990s, the Washington Consensus (i.e., the set of policies advocated by that time by the Washington-based institutions IMF, World Bank, and US Treasury) had been prescribing policies that included the liberalization of financial relations as a cornerstone of a wider program that was supposed to promote economic growth in developing countries. Many of those countries ended up suffering financial crises. Empirical research has shown a clear relationship between financial liberalization and financial instability. Using an extensive dataset that incorporates seven dimensions of financial reforms, I show how each of them has contributed to higher financial instability, how the effects have been mainly concentrated in the short-term, and how liberalizations have led to bifurcation paths across countries – while some countries could increase their levels of productivity permanently, several others only experienced an expectation of permanent increases in productivity at the time of the reforms, but never experienced the actual increases, finalizing with crises as the consequence of overborrowing. I describe how these facts can be explained by two theoretical mechanisms that interact with each other. The first mechanism is the problem of identification of productivity trends, that becomes more relevant after sizeable financial reforms. The second mechanism is related to informational problems.

Chapter 3 changes the focus of the analysis of financial crises from their causes to their effects. I have been working on this project with my advisor Professor Peter Howitt since the second year of my PhD program. A year later, Pablo Gluzmann joined us during the XI Trento Summer School on Macroeconomics and Financial Crises, where Peter, Pablo, and I stayed in the same Conference Center for two weeks. We analyze the empirical validity of part of the so-called Financial Instability Hypothesis (FIH), established by Professor Hyman Minsky. One part of the FIH states that the longer the span of time since the last crisis, the more severe is the new crisis when it comes. The reason 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. Indeed, we obtain that banking and sovereign debt crises tend to be more severe when they occur after long periods of stability. This is not the case for inflation and currency crises: They tend to be more severe after periods of higher volatility of expectations.

It is my hope that this dissertation contributes to a deeper understanding of the causes and effects of financial crises. Personally, I hope writing this dissertation prepared me to learn faster and with more precision, in a field in which there is so much to learn, to actively contribute to shape the economic thought on the macroeconomic issues that concern the world and especially my region, Latin America, in ways that help our societies to pursue policies that make the world a better place to live in.

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Chapter 1

Overborrowing Crises and The Role of Expectations

1.1 Introduction

This paper studies the role of expectations and learning in the occurrence of crises that involve massive defaults, either in the private sector (banking crises) or the public sector (sovereign debt crises). This family of crises will be called “overborrowing crises.” The frequency of overborrowing crises is high in emerging economies but low in developed economies. A high frequency of crises requires a large variance of expected permanent income. Compared to a benchmark with full information rational expectations (FIRE), models with learning about productivity trends display a higher variance of expected permanent income in emerging economies, but a similar one in developed economies. Thus, I show that models with learning improve the match between theoretical and empirical frequencies of overborrowing crises in emerging economies with respect to the FIRE benchmark.

For the occurrence of overborrowing crises, expectations matter. Crises are trig-

gered when there are large negative shocks to expected permanent income. Reinhart and Rogoff (2009) document that overborrowing 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. Nevertheless, the model with FIRE underpredicts the actual frequency of these events in emerging economies. By incorporating imperfect information and learning about productivity trends, I show that the model can account for this high frequency of large negative shocks to expected permanent income in emerging economies. Moreover, this modified framework still generates the same satisfactory results that the FIRE benchmark obtains for developed economies.

In this paper, I explore the role that learning about productivity trends plays in the occurrence of overborrowing crises within a quantitative model of default of a small open economy, building on Aguiar and Gopinath (2006) and Eaton and Gersovitz (1981). In this model, expectations about future output are the key determinant of the present discounted value (PDV) of the agent's utility associated with each of the two possible actions, "default" and "no default." If the agent defaults on her debt, she loses access to credit, although in every period after defaulting, there is a positive probability that she will be able to borrow again. If the agent does not default, she has access to credit markets. A default crisis occurs when the PDV of the agent's utility in the case where she defaults on her debt is greater than in the case where she repays the debt. Output is exogenous and stochastic, and it is characterized by transitory and permanent shocks. Permanent shocks have a greater effect than transitory shocks on the value function associated with no default. Hence, a negative permanent shock increases the probability of default by more than a negative transitory shock of the same size.

The agent forms beliefs about the type of shocks the economy receives based upon the available information about the nature of shocks, and on the mechanism she uses to process that information in order to form expectations. This paper analyzes three mechanisms for formation of beliefs: full-information rational expectations (FIRE), Bayesian learning of a Kalman filter type, and non-Bayesian stochastic gain learning.

The first mechanism is based on the FIRE assumption. Under this assumption, the agent can perfectly identify whether changes in output are due to transitory or permanent shocks.

The second mechanism is the consequence of modifying the structure of information by assuming that the agent cannot identify the type of shocks the economy receives. Instead, she uses the Kalman filter to learn about the nature of output shocks, where the Kalman coefficients are derived from her knowledge of the stochastic properties of the productivity processes. Survey data on GDP growth expectations by the Survey of Professional Forecasters of Consensus Forecasts reveals two facts that motivate the analysis of the role of learning under imperfect information: (i) in emerging market economies the sample mean of forecasting errors differs significantly from zero; and (ii) first order autocorrelations of forecast errors are positive and significant for the cases of Argentina (0.89) and Mexico (0.25). This sample evidence does not support the two conditions that must be satisfied under the null hypothesis of FIRE, i.e., that the mean of forecast errors be equal to zero and that forecast errors be not serially correlated. Although with this short sample we cannot tell whether these deviations from FIRE come from the full information (FI) side or the rational expectations (RE) side, 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.

This type of Bayesian learning increases the variance of perceived shocks to perma-

nent income with respect to the FIRE benchmark. The increase is larger for emerging economies. There are two causes for the above effects. Firstly, every time the economy receives an aggregate growth shock, the agent can update her beliefs on its three components: the contemporaneous permanent component, the contemporaneous cyclical component, or the previous period's cyclical component. As a result, every time the agent revises her belief on the previous period's cyclical shock, she is also revising her belief on the contemporaneous permanent shock in the opposite direction, increasing the variance of beliefs of permanent shocks. Secondly, the share of the aggregate shock attributed to the permanent component is increasing in the relative variability of permanent shocks. This variability is larger for emerging economies. A higher variance of perceived shocks to permanent income is associated with a higher probability of negative shocks large enough to trigger a default. Therefore, this learning mechanism increases the frequency of crises by a larger amount in emerging economies than in more stable developed economies.

The third mechanism is a non-Bayesian learning algorithm called stochastic-gain learning (SGL). The Bayesian Kalman filter learning maintains the assumption of RE but does not maintain the assumption of FI, while the SGL explores the consequences of maintaining neither FI nor RE. The structure of information is the same for both learning mechanisms. However, unlike when using the Kalman filter, agents do not use information optimally when using a SGL algorithm. They do not decompose aggregate growth shocks into permanent and transitory. Instead, they follow a simple rule to form expectations about the future aggregate growth rate of output. If forecast errors are small, the individual adjusts her expectations by using a decreasing gain parameter. If forecast errors are large, the individual suspects there was a change of regime and uses a constant gain parameter, which assigns more importance to information of the present.

The motivation for analyzing a non-Bayesian learning mechanism for the formation of beliefs comes both from empirical and theoretical considerations. On the empirical side, I consider two noteworthy facts: (i) The above-mentioned evidence from survey data on GDP growth expectations shows that the conditions that must be satisfied under the null of FIRE do not hold for emerging economies; and (ii) survey data on GDP growth expectations for emerging economies is better matched by non-Bayesian learning of a SGL type than by either FIRE or Bayesian Kalman filter learning. This evidence is described in Section 3. On the theoretical side, the SGL, inspired by the discussion in Sargent (1993), allows for the analysis of a situation in which there are unexpected events that change the current status quo permanently to a state that is not well-defined for the individual. The new reality is learned only after the event has occurred. By using a SGL algorithm, the agent is then able to track changes in the environment without knowing exactly what the nature of those changes may be. Equally importantly, SGL satisfies a set of desirable conditions that imply good forecasts along the transition and asymptotically. These conditions are described in section (1.3).

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. 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.

The models presented are calibrated for two emerging economies (Argentina and Mexico) and one developed economy (Canada). The choice of these countries is made to allow for a comparison with results established in the literature. Overall, my results show that models with learning, especially the stochastic-gain learning algorithm, produce: (1) higher theoretical frequencies of crises, improving the match with the actual frequencies in comparison to the full information rational expectations benchmark; and (2) an even sharper improvement in the match for emerging economies. These findings suggest that learning plays a key role in the occurrence of overborrowing crises and that its quantitative importance is higher in emerging economies.

1.1.1 Related Literature

This paper is related to three strands of literature.

The first strand deals with models of strategic default. The approach I adopt builds on the Dynamic and Stochastic General Equilibrium version of Eaton and Gersovitz (1981) proposed by Aguiar and Gopinath (2006). My distinction is on the emphasis of learning and interpretation of signals under imperfect information. In order to obtain theoretical frequencies of crises that match the actual frequencies of crises

of emerging economies in the FIRE model, it is necessary to have a large variance of the permanent component of shocks to productivity. In another related paper, Aguiar and Gopinath (2007) document a high volatility of growth trends in emerging markets. They identify permanent shocks to productivity by using the Permanent Income Hypothesis applied to short time-series samples. On the other hand, Garcia Cicco et al. (2010) perform an econometric estimation of the parameters that govern the productivity processes by using long time-series, and obtain a significantly lower variance of the permanent component of growth shocks for emerging economies than Aguiar and Gopinath (2007) do. With the parameters obtained by following the long time-series methodology, the variance of permanent income is not large enough to satisfactorily explain the actual frequency of overborrowing crises (I show this fact in section 2). The introduction of imperfect information and learning moderates the need for a high variance of permanent shocks to produce a good matching with actual data on the frequency of crises.

The second strand is the literature on learning in macroeconomics. Evans and Honkapohja (2001) extensively analyze the role of learning and expectations in macroeconomics. Boz et al. (2011) is the main antecedent for the introduction of Bayesian learning in which agents use the Kalman filter to decompose aggregate growth shocks into permanent and transitory. They show that such a learning mechanism contributes to the explanation of the excessive volatility of consumption with respect to output and the strongly countercyclical trade balances in emerging economies. On the other hand, stochastic-gain learning and constant-gain learning have also been utilized to address macroeconomic instability phenomena. Motivated by Sargent (1993), Marcet and Nicolini (2003) use constant-gain learning to explain facts associated to hyperinflations, while Milani (2007) introduces it in a Dynamic and Stochastic General Equilibrium framework to match the persistence in macroeconomic variables. I show that these tools contribute to the explanation of the high frequencies of over-

borrowing crises in emerging economies.

The third strand is the literature on models of “news shocks,” such as Jaimovich and Rebelo (2009) and Schmitt-Grohé and Uribe (2008), which emphasizes the role of expectations for business cycle dynamics. In this paper, permanent shocks to productivity are like news about the future. Revisions of beliefs about the permanent component of aggregate growth shocks have similar qualitative effects as news shocks.

1.2 A baseline model of overborrowing crises

This section presents a model of strategic default that tries to match the actual frequencies of overborrowing crises. The basic framework is introduced in Eaton and Gersovitz (1981) and Aguiar and Gopinath (2006). While Aguiar and Gopinath (2006) focus on the importance of permanent shocks to productivity to explain the frequency of crises, I focus on the role of beliefs about the type of shocks and expectations about future output.

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 Γ_t :

$$Y_t = e^{z_t} \Gamma_t \tag{1.2.1}$$

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

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

$$z_t = \rho_z z_{t-1} + \epsilon_t^z \tag{1.2.2}$$

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

Cumulative permanent shocks g_t are described by

$$g_t = (1 - \rho_g)\mu_g + \rho_g g_{t-1} + \epsilon_t^g \quad (1.2.3)$$

with $|\rho_g| \in (0, 1)$ and $\epsilon_t^g \sim N(0, \sigma_g^2)$. ρ_g and σ_g^2 represent the persistence and the variance of the permanent shocks, respectively. μ_g is the steady state growth rate of output. For the simulations, I assign to μ_g the historical average quarterly growth rate of output for each country.

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:

$$u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma} \quad (1.2.4)$$

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

$$V^G(d_t, \tilde{z}_t, \tilde{g}_t) = \max_{\{c_t\}} \{u(c_t) + \beta E_t V(d_{t+1}, \tilde{z}_{t+1}, \tilde{g}_{t+1})\} \quad (1.2.5)$$

subject to

$$c_t = y_t - d_t + q_t d_{t+1} \quad (1.2.6)$$

where β 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 δ that is lost due to defaulting. With probability λ 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

$$V^B(\tilde{z}_t, \tilde{g}_t) = u[(1 - \delta)y_t] + \beta[\lambda E_t V(0, \tilde{z}_{t+1}, \tilde{g}_{t+1}) + (1 - \lambda)E_t V^B(\tilde{z}_{t+1}, \tilde{g}_{t+1})] \quad (1.2.7)$$

The default function is given by

$$D(d_t, z_t, g_t) = 1 \text{ if } V^B(z_t, g_t) > V^G(d_t, z_t, g_t) \quad (1.2.8)$$

and zero otherwise.

The capital market is composed of risk-neutral international investors whose oppor-

tunity cost is the risk-free interest rate r^* . Then, the equilibrium condition in the capital market must satisfy

$$q(d_{t+1}, z_t, g_t) = \frac{E_t(1 - D_{t+1})}{1 + r^*} \quad (1.2.9)$$

1.2.1 A note on overborrowing crises

The challenge of the model is to match the empirical frequency of overborrowing crises. In the model, the crisis is the default.

Tables (1.1) and (1.2) show the actual frequencies of overborrowing crises for developed and emerging countries after the second World War, compiling data from Reinhart and Rogoff (2009) and Laeven and Valencia (2012). I define an overborrowing crisis as either a banking crisis or a sovereign debt crisis. The rationale for this definition is to include crises that involve massive defaults, either in the private sector (banking crises) or the public sector (sovereign debt crises). Overborrowing crises are more frequent in emerging economies. The average frequency of crises in developed countries is 0.025 (one crisis every 40 years), while in emerging economies is 0.05 (one crisis every 20 years). Besides, in developed economies the overborrowing crises are almost exclusively banking crises.

To match the frequency of crises in emerging economies, the model must generate a sufficiently large variance of expected permanent income. Next, I explore how different mechanisms for formation of expectations tackle this problem.

1.2.2 Formation of beliefs I: Full Information Rational Expectations

Full information rational expectations (FIRE) is the case presented in Aguiar and Gopinath (2006). 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). Also, 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 $Pr(g_{t+1} = g_i/g_t = g_j)$. With FIRE, in the value functions the beliefs on contemporaneous shocks are always correct: $\tilde{z}_t = z_t$ and $\tilde{g}_t = g_t$.

Aguiar and Gopinath (2006) claim that the FIRE model with permanent shocks to productivity can account for the actual frequency of default crises in emerging economies. In order to produce a good match between the theoretical and the empirical frequency of default crises, the model requires a sufficiently large variance of permanent shocks to productivity. Aguiar and Gopinath (2007) estimate the parameters that govern the productivity processes by using the Permanent Income Hypothesis (PIH), and conclude that the variance of permanent shocks is large enough to account for the frequency of crises in emerging economies. However, Garcia Cicco, Pancrazzi, and Uribe (2010) reestimate those parameters by using “long” time-series and obtain significantly lower variance of permanent shocks. When the model is fed with the parameters calculated by following the long time-series methodology, there are drastic changes in the results with respect to those reported by Aguiar and Gopinath (2006).

The model is simulated choosing values for the structural parameters that go in line with the values conventionally used in the literature. Table (1.3) reports those values.¹ Tables (1.4) to (1.6) show the values of the productivity processes parameters for each

¹All tables and figures are shown in the appendix.

of the two parametrizations, the one that comes from using the PIH and the one that comes from performing an estimation by using long time-series, for Argentina, Mexico, and Canada. Table (1.7) shows the results for the frequency of crises for the two different parametrizations. Both in Argentina and Mexico the theoretical frequency of crises reduces from 2 percent to 0. In Canada, the frequency was indistinguishable from zero with Aguiar and Gopinath parametrization, and it remains the same with the proposed reparametrization.

In conclusion, 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. The rest of the paper explores how learning mechanisms can improve this match.

1.3 Introducing Learning about Productivity Trends

1.3.1 Are actual expectations consistent with the FIRE assumption?

Expectations matter. How much to borrow is just one of the fundamental decisions underlying macroeconomic dynamics that hinge upon agents expectations about future income. Yet how those expectations are formed, and how best to model this process, remains an open question. This question has been addressed, among others, by Coibion and Gorodnichenko (2010).

Full information rational expectations (FIRE) is the most accepted and utilized hypothesis on expectations formation in the macroeconomics literature. However, 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. Argentina and Mexico belong to the set of countries for which data is available, but Canada is not. However, the survey offers data for other developed countries that exhibit levels of macroeconomic volatility similar to Canada, like Australia.

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

$$g_{t+1}^y = E_t g_{t+1}^y + \epsilon_{t+1} \quad (1.3.1)$$

with

$$E(\epsilon_{t+1}) = 0 \quad \& \quad E(\epsilon_t \cdot \epsilon_{t+1}) = 0 \quad \forall t > 0 \quad (1.3.2)$$

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 Argentina, Mexico, and Australia, we obtain (see table (1.8)):

1. The sample mean of forecast errors is significantly different from zero in Argentina, but it is not significantly different from zero in Mexico and Australia.
2. First order autocorrelations of forecast errors are positive and significant in Argentina and Mexico, but not significantly different from zero in Australia. 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. This paper does both. By exploring these alternative learning mechanisms, I can assess the economic significance of deviations from FIRE for explaining overborrowing crises.

1.3.2 Learning and identification of output trends

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 (1.1) and (1.2) 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 proposed in this paper capture this intuition. As explained below, both Bayesian learning and non-Bayesian learning will exhibit more volatile expectations with respect to the FIRE benchmark in emerging economies than in stable developed economies.

1.3.3 Formation of beliefs II: Rational Expectations with Imperfect Information (Kalman Filter Learning)

This section assumes that the agent is imperfectly informed about the true decomposition of the aggregate growth shocks the economy receives. The aggregate shocks are the signals she must interpret. She attempts to identify whether changes in output are due to transitory or permanent shocks by using the Kalman filter. This is the rational expectations approach in a context of imperfect information on the nature of shocks.

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

$$g_t^Y = \ln\left(\frac{Y_t}{Y_{t-1}}\right) = \begin{bmatrix} 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} z_t \\ z_{t-1} \\ g_t \end{bmatrix} \quad (1.3.3)$$

with

$$\begin{bmatrix} z_t \\ z_{t-1} \\ g_t \end{bmatrix} = \begin{bmatrix} \rho_z & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho_g \end{bmatrix} \begin{bmatrix} z_{t-1} \\ z_{t-2} \\ g_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ (1 - \rho_g)\mu_g \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^z \\ \epsilon_t^g \end{bmatrix} \quad (1.3.4)$$

I work with the following notation:

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

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

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

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_t^Y :

$$a_t = k_1 a_{t/t-1} + k_2 g_t^y \quad (1.3.5)$$

where

$$k_1 = I - PZ'(ZPZ')^{-1}Z \quad (1.3.6)$$

$$k_2 = PZ'(ZPZ') \quad (1.3.7)$$

and

$$a_{t/t-1} = Ta_{t-1} + c \quad (1.3.8)$$

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:

$$P = TPT' - TPZ'(ZPZ')^{-1}ZPT' + RQR' \quad (1.3.9)$$

$a_t = \begin{bmatrix} \tilde{z}_t & \tilde{z}_{t-1} & \tilde{g}_t \end{bmatrix}'$ 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.

How does Bayesian Kalman filter learning affect the likelihood of a crisis?

To understand how this type of learning affects the probability of an overborrowing 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 $|\frac{\partial V^G}{\partial z_t} - \frac{\partial V^B}{\partial z_t}|$? The answer is that the value of that difference is “small”. To see why, firstly suppose z -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 $|\frac{\partial V^G}{\partial g_t} - \frac{\partial V^B}{\partial g_t}|$? 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 due to the 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

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

Under Bayesian learning, the decomposition is given by

$$g_t^y = \ln\left(\frac{Y_t}{Y_{t-1}}\right) = \tilde{z}_t - \tilde{z}_{t-1} + \tilde{g}_t$$

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 Ar-

gentina, the annual rates of output growth, g_t^y , from 1998 to 2000, were the following: $g_{1999}^y = -0.03$ and $g_{2000}^y = -0.01$. Let g_t and z_t denote the beliefs about the permanent and transitory component of the aggregate shock g_t^y , 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. The variance of permanent shocks is larger for Argentina and Mexico than for Canada. Hence, learning increases the frequency of crises by a larger amount in Argentina and Mexico than in Canada

Results

Table (1.9) shows the frequency of default crises with Kalman filter learning for each parametrization. While for Canada the frequencies are indistinguishable from the ones obtained in the FIRE model, for Argentina and Mexico we observe noticeable changes: with Bayesian learning of a Kalman filter type, theoretical frequencies of

countries are higher for those countries than in the FIRE benchmark, producing a better match with actual frequencies. However, the discrepancies between theoretical and actual frequencies are still large.

1.3.4 What theoretical expectations have a better fit to actual expectations?

I address this question by calculating the average sum of squared differences between actual expectations and theoretical expectations on GDP per capita growth that come from the three mechanisms for formation of expectations analyzed in this paper: the already presented FIRE and Bayesian Kalman filter learning, and a non-Bayesian learning algorithm called stochastic-gain learning. Actual expectations are represented by survey data from the Survey of Professional Forecasters. This exercise is performed for Argentina and Mexico. It is not performed for Canada due to the lack of survey data on expectations in the SPF database.

There are different paths of expectations that satisfy the conditions that FIRE requires under the null, i.e., a zero mean and no serial autocorrelation of forecast errors. Perfect foresight is one of those paths, and it is the one I will use to calculate how accurate is FIRE as a representation of actual expectations. With perfect foresight, the series of expectations is given by

$$E_t g_{t+1}^y = g_{t+1}^y \tag{1.3.10}$$

With Bayesian Kalman filter learning, I construct a series of theoretical expectations as follows. Firstly, I use the decomposition of aggregate shocks into transitory and permanent shocks according to (1.3.5). This step requires the definition of a prior

belief. I assume that the prior belief is such that $z_0 = g_t^0 - \mu_g$, i.e., the agent considers that the initial deviation of the growth rate of output from its steady state is due to a transitory shock. Secondly, I obtain an expectation for the next period's transitory and permanent shocks according to the equations that govern the shock processes, (1.2.2) and (1.2.3). Given z_t and g_t , the expectations about z_{t+1} and g_{t+1} are given by

$$E_t(z_{t+1}) = \rho_z z_t \quad (1.3.11)$$

and

$$E_t(g_{t+1}) = (1 - \rho_g)\mu_g + \rho_g g_t \quad (1.3.12)$$

Finally, I obtain the expectation for the next period's aggregate growth rate as follows:

$$E_t(g_{t+1}^y) = E_t(g_{t+1} + z_{t+1} - z_t) = (1 - \rho_g)\mu_g + \rho_g g_t + (\rho_z - 1)z_t \quad (1.3.13)$$

In every period t a new expectation is formed for period $t + 1$.

The third series of theoretical expectations is constructed by using a non-Bayesian learning algorithm called stochastic-gain learning (SGL). With SGL, the agent does not decompose aggregate growth shocks into permanent and transitory. Instead, she follows a simple rule to form expectations about the future aggregate growth rate of output. If forecast errors are small, the individual adjusts her expectations by using a decreasing gain parameter. If forecast errors are large, the individual suspects there was a change of regime and uses a constant gain parameter, which assigns more importance to information of the present. Analytically, SGL is represented by

$$E_t g_{t+1}^y = E_{t-1} g_t^y + \kappa_t (g_t^y - E_{t-1} g_t^y) \quad (1.3.14)$$

$$\kappa_t = \begin{cases} 1/t & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1}g_{t-s}^y|) < v_t^y \\ \kappa & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1}g_{t-s}^y|) \geq v_t^y \end{cases} \quad (1.3.15)$$

where 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 $\frac{1}{\kappa^{-1}+t}$ ($t = 1$ one after the switch).

The construction of a series of expectations with SGL is more mechanic than with Kalman filter learning. This mechanism also requires a prior belief, which is set as the perfect foresight expectation, $E_0g_1^y = g_1^y$.

SGL also needs values for two additional parameters: the constant-gain κ , and the relevant time horizon for comparing recent forecast errors with historical forecast errors, S . I choose $S = 3$, which means that the individual compares the historical forecast errors with the average forecast errors of the last three years. The results obtained are robust to any choice of S from 1 to 5. The parameter κ_i is chosen optimally for every country i . Optimality in this context means that κ_i is the value that minimizes the sum of squared differences between expectations and realizations:

$$\text{Min}_{\{\kappa_i\}} \sum_{t=0}^T (E_t g_{i,t+1}^y - g_{i,t+1}^y)^2 \quad (1.3.16)$$

For Argentina I obtain $\kappa = 1.25$, and for Mexico I obtain $\kappa = 1.08$.

Let SS_i^j be the average sum of squared differences between theoretical expectations and actual expectations for country i for the mechanism j , where j can be perfect foresight, Kalman filter learning, or SGL:

$$SS_i^j = \frac{1}{T} \sum_{t=0}^T (E_t g_{i,t+1}^{y,j} - g_{i,t+1}^y)^2 \quad (1.3.17)$$

where $E_t g_{i,t+1}^{y,j}$ is the expectation at time t for the growth rate of per capita GDP between t and $t+1$, for country i under the mechanism j , and $E_t g_{i,t+1}^y$ is the expectation at time t for the growth rate of per capita GDP between t and $t+1$, for country i , that comes from survey data.

Table (1.10) shows the values of SS_i^j . In Argentina, the ranking in terms of best fit with actual expectations is the following: (1) SGL; (2) Perfect Foresight; (3) Kalman filter learning. In Mexico, the ranking is the following: (1) Perfect Foresight; (2) SGL and Kalman filter learning, which are indistinguishably good according to the measure SS_i^j . Figures (1.3) and (1.4) show the evolution of expectations for the three mechanisms and for survey data for Argentina and Mexico, respectively.

The superior performance of non-Bayesian learning to explain actual data on expectations motivates its use for explaining the frequency of overborrowing crises, a task done in the next section.

1.3.5 Formation of beliefs III: Stochastic-gain learning

I assume that the agent does not decompose aggregate growth shocks into permanent and transitory. Instead, she forms expectations about the next period's aggregate growth shock according to the SGL mechanism described in (1.3.14) and (1.3.15). In this learning scheme, the individual does not take into account the fact that in the subsequent periods she will keep updating her expectations.

The value functions become:

$$V^G(d_t, g_t^y) = \max_{\{c_t\}} \{u(c_t) + \beta E_t V(d_{t+1}, g_{t+1}^y)\} \quad (1.3.18)$$

subject to the budget constraint $c_t = y_t - d_t + q_t d_{t+1}$, and

$$V^B(g_t^y) = u[(1 - \delta)y_t] + \beta[\lambda E_t V(0, g_{t+1}^y) + (1 - \lambda)E_t V^B(g_{t+1}^y)] \quad (1.3.19)$$

with $V = \max\{V^G, V^B\}$

How does stochastic-gain learning affect the likelihood of a crisis?

SGL increase 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 1.5 shows two different paths of expectations constructed by assuming 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.

Theoretical properties of SGL

As shown in Marcet and Nicolini (2003), SGL satisfies a set of lower bound conditions on rationality that imply that forecasts are good along the transition and asymptotically. Those lower bounds are named asymptotic rationality, epsilon-delta rationality, and internal consistency.

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:

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

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

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 .

AR is a requirement that only rules out behavior that is inconsistent forever, hence assures good forecasts in the limit. However, it admits learning mechanisms that generate bad forecasts along the transition for many periods. EDR and IC assure forecasts during the transition are good. They are studied only for “moderately high” values of T .

Results

SGL requires to assign values to two additional parameters: κ and S . For these simulations in which the periods are quarters, I choose $\kappa = 0.01$ and $S = 12$, for every country. The choice of S means that the agent compares average forecast errors of the last 12 quarters with historical forecast errors to determine the choice of the gain parameter.

Table (1.11) shows the frequency of default crises with SGL for each parametrization. The frequencies of crises increase in the three countries, both with respect to FIRE and Kalman filter learning. However, the increases are larger in emerging economies. SGL improves the match with actual frequencies.

Robustness

The proper values for κ and S may differ across countries. Countries that experience more frequent and more drastic changes of regimes may find convenient to assign more importance to present information when those regime changes occur. To analyze the robustness of the previous results, I assign a different value κ_i for each country i , such that κ_i minimizes the sum of squared forecast errors, i.e., κ_i is the solution to (1.3.16). Table (1.12) shows the resulting values of κ_i . This value is higher for Argentina than for Mexico than for Canada. Assigning these values to the model reinforces the obtained results, increasing the frequency of crises by even more in Argentina than in Mexico and in Mexico than in Canada with SGL with respect to the other mechanisms for formation of expectations.

Results are also robust to different choices of S . Choosing S equal to 4, 8, 16, or 20 does not alter the pattern of results.

1.4 Conclusions

Table (1.13) summarizes the main results of the paper. The model of overborrowing crises with full information rational expectations (FIRE) requires a large variance of permanent shocks to productivity to account for the actual frequency of overborrowing crises in emerging economies. Instead, the low frequency of crises of developed economies is consistent with the observed low variance of permanent shocks to productivity. When estimated by using a long time-series sample for emerging economies, the variance of permanent shocks in emerging economies is too low to allow for a good match of the actual and theoretical frequencies of crises predicted by the FIRE model for those countries.

The introduction of learning increases the perceived variance of permanent shocks in emerging economies, but it does not alter that variance in developed economies. Hence, models with learning can better match the actual frequencies of overborrowing crises in emerging economies than the model with FIRE. The improve in the match is greater when using a stochastic-gain learning algorithm than when using a rational expectations approach with imperfect information, in which the agent uses the Kalman filter to decompose aggregate growth shocks into transitory and permanent.

1.5 Appendix: Tables and Figures

Table 1.1: Frequencies of crises, developed countries

Country	BC	Freq. BC	SDC	Freq. SDC	OBC	Freq. OBC
Australia	1	0.015	0	0	1	0.015
Austria	1	0.015	0	0	1	0.015
Belgium	1	0.015	0	0	1	0.015
Canada	1	0.015	0	0	1	0.015
Denmark	2	0.03	0	0	2	0.03
Finland	1	0.015	0	0	1	0.015
France	2	0.03	0	0	2	0.03
Germany	2	0.03	0	0	2	0.03
Greece	2	0.03	0	0	2	0.03
Iceland	3	0.047	0	0	3	0.047
Ireland	1	0.015	0	0	1	0.015
Italy	1	0.015	0	0	1	0.015
Japan	1	0.015	0	0	1	0.015
Korea	3	0.047	0	0	3	0.047
Netherlands	1	0.015	0	0	1	0.015
New Zealand	1	0.015	0	0	1	0.015
Norway	1	0.015	0	0	1	0.015
Portugal	1	0.015	0	0	1	0.015
Spain	2	0.03	0	0	2	0.03
Sweden	1	0.015	0	0	1	0.015
Switzerland	1	0.015	0	0	1	0.015
United Kingdom	5	0.078	0	0	5	0.078
United States	2	0.03	0	0	2	0.03
Average	1.6	0.025	0	0	1.6	0.025

Sources: Reinhart and Rogoff (2009) and Laeven and Valencia (2012)

Table 1.2: Frequencies of crises, emerging countries

Country	BC	Freq. BC	SDC	Freq. SDC	OBC	Freq. OBC
Argentina	4	0.06	5	0.08	6	0.09
Brazil	4	0.06	4	0.06	4	0.06
Chile	2	0.03	6	0.09	6	0.09
China	1	0.015	0	0	1	0.015
Colombia	2	0.03	0	0	2	0.03
Egypt	2	0.03	1	0.015	2	0.03
Hungary	2	0.03	0	0	2	0.03
India	2	0.03	3	0.047	5	0.08
Indonesia	3	0.047	3	0.047	4	0.06
Malaysia	2	0.03	0	0	2	0.03
Mexico	2	0.03	1	0.015	2	0.03
Morocco	1	0.015	2	0.03	2	0.03
Peru	2	0.03	5	0.08	6	0.09
Philippines	2	0.03	1	0.015	2	0.03
Poland	1	0.015	1	0.015	1	0.015
Singapore	1	0.015	0	0	1	0.015
South Africa	2	0.03	3	0.047	4	0.06
Sri Lanka	1	0.015	3	0.047	4	0.06
Taiwan	3	0.047	0	0	3	0.047
Thailand	2	0.03	0	0	2	0.03
Turkey	4	0.06	5	0.08	7	0.11
Uruguay	3	0.047	5	0.08	6	0.09
Venezuela	2	0.03	4	0.06	4	0.06
Average	2.17	0.03	2.26	0.035	3.4	0.05

Sources: Reinhart and Rogoff (2009) and Laeven and Valencia (2012)

Table 1.3: Parameters for the overborrowing crises model

Parameter	Value	Concept
ρ_z	AG/GCPU	Persistence of transitory shocks
ρ_g	AG/GCPU	Persistence of permanent shocks
σ_z^2	AG/GCPU	Variance of transitory shocks
σ_g^2	AG/GCPU	Variance of permanent shocks
μ_g	Country-specific	Average output growth rate
σ	2	CRRA
β	0.98	Discount factor
δ	0.02	Static cost of default
λ	0.1	Redemption probability
r^*	0.01	Risk-free interest rate

Table 1.4: Productivity parameters, Argentina

Argentina	ρ_g	ρ_z	σ_g	σ_z
AG	0.17	0.9	0.03	0.034
GCPU	0.35	0.87	0.0071	0.033

Table 1.5: Productivity parameters, Mexico

Mexico	ρ_g	ρ_z	σ_g	σ_z
AG	0.11	0.9	0.0255	0.0054
GCPU	0.247	0.019	0.017	0.019

Table 1.6: Productivity parameters, Canada

Canada	ρ_g	ρ_z	σ_g	σ_z
AG	0.29	0.97	0.0047	0.0063
GCPU	0.36	0.91	0.0052	0.0049

Table 1.7: Theoretical Frequencies of crises with FIRE

Country	AG Parameters	GCPU Parameters	Empirical freq.
Argentina	0.0190	≈ 0	0.094
Mexico	0.01674	0.0004	0.031
Canada	≈ 0	≈ 0	0.015

Table 1.8: Forecast errors

Country	Observations	Mean	Autocorrelation
Argentina	26	-0.92*	0.89*
Mexico	33	0.04	0.25*
Australia	33	-0.01	0.16

Sources: ECLAC, INE-Mexico, and Bloomberg. * Significantly different from 0 at the 10% level.

Table 1.9: Theoretical Frequencies of crises with Kalman filter learning

Country	AG Parameters	GCPU Parameters	Empirical freq.
Argentina	0.031	0.0026	0.094
Mexico	0.0202	0.0049	0.031
Canada	≈ 0	≈ 0	0.015

Table 1.10: Average sum of squares of differences in actual and theoretical expectations

Country	SS(PF)	SS(KF)	SS(SGL)
Argentina	12.9	30.7	9.1
Mexico	0.5	3.7	3.7

Note: PF: Perfect Foresight; KF: Kalman filter learning; SGL: Stochastic-Gain Learning

Table 1.11: Theoretical Frequencies of crises with SGL

Country	AG Parameters	GCPU Parameters	Empirical freq.
Argentina	0.0660	0.044	0.094
Mexico	0.033	0.051	0.031
Canada	0.0002	0.0006	0.015

Table 1.12: Country-specific constant-gain

Country	Optimal constant-gain (κ)
Argentina	0.042
Mexico	0.012
Canada	0.005

Table 1.13: Summary of results - Frequencies of overborrowing crises

Country	AG Parameters	GCPU Parameters	Empirical freq.
Argentina(1)	0.0190	≈ 0	0.094
Argentina(2)	0.031	0.0026	0.094
Argentina(3)	0.0660	0.044	0.094
Mexico(1)	0.01674	0.0004	0.031
Mexico(2)	0.0202	0.0049	0.031
Mexico(3)	0.033	0.051	0.031
Canada(1)	≈ 0	≈ 0	0.015
Canada(2)	≈ 0	≈ 0	0.015
Canada(3)	0.0002	0.0006	0.015

Note for tables: AG refers to Aguiar and Gopinath (2007)'s methodology. GCPU refers to Garcia-Cicco, Pancrazi, and Uribe (2010)'s methodology.

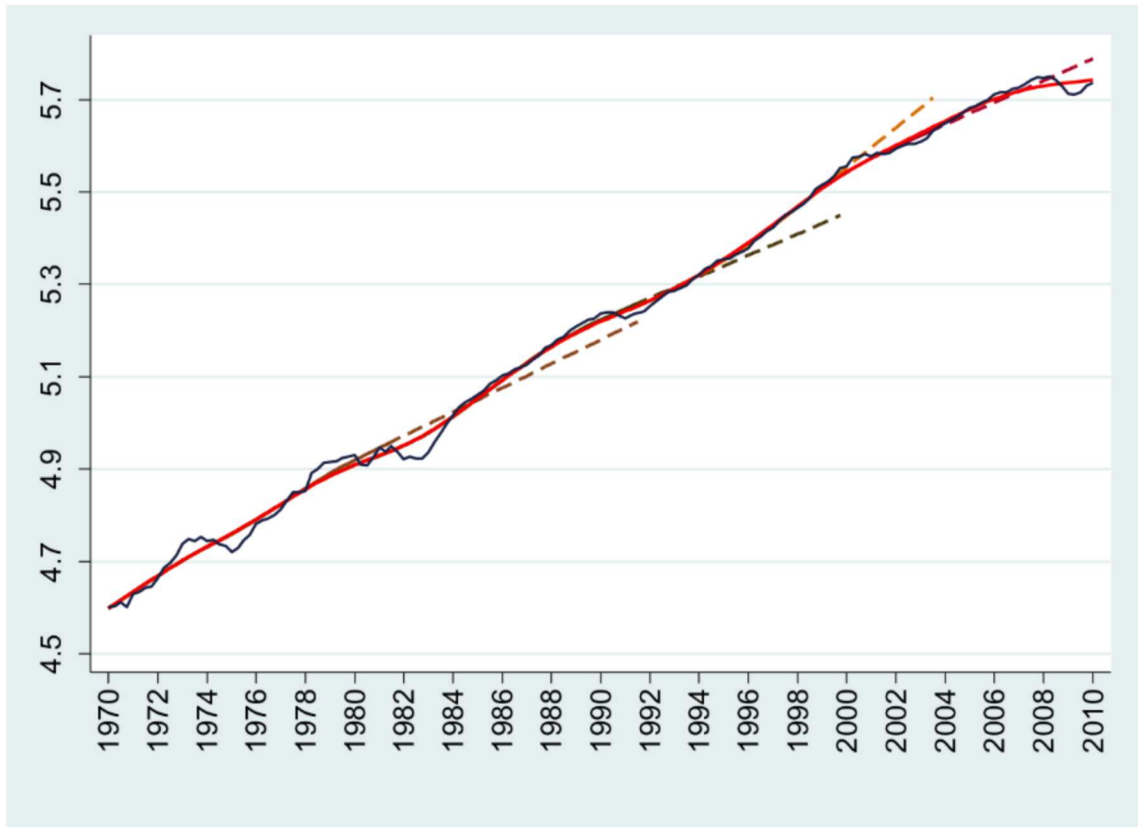


Figure 1.1: Recursive GDP per capita trends, United States

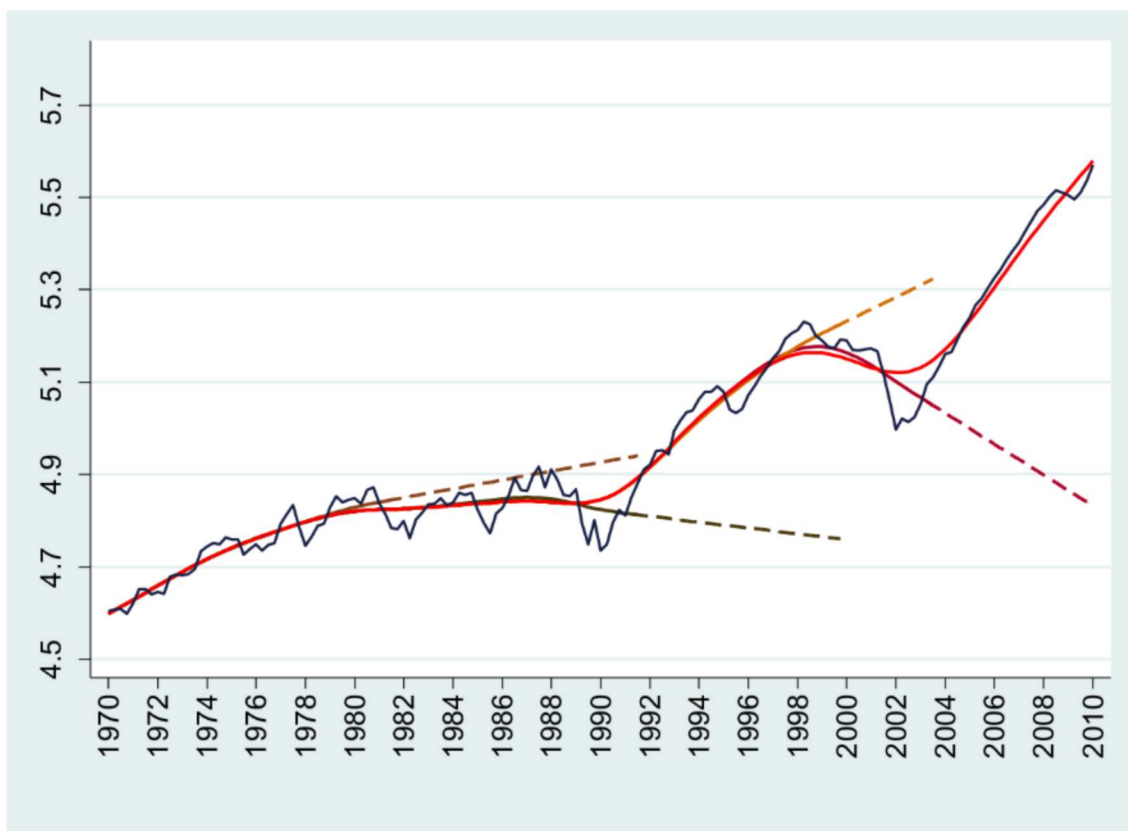


Figure 1.2: Recursive GDP per capita trends, Argentina

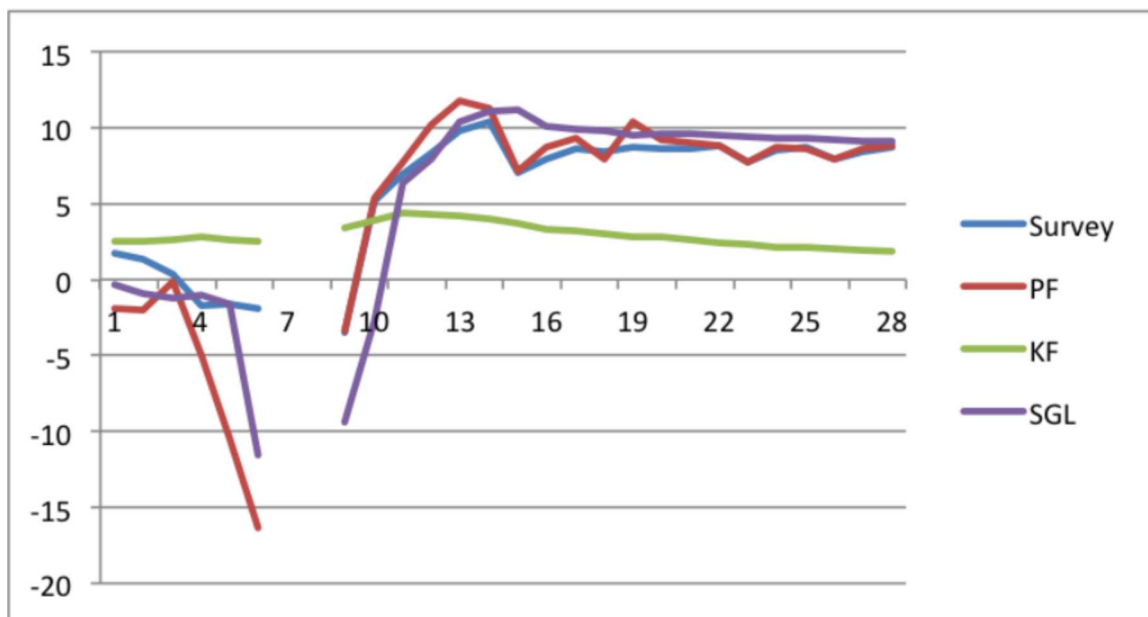


Figure 1.3: Paths of output growth expectations, Argentina

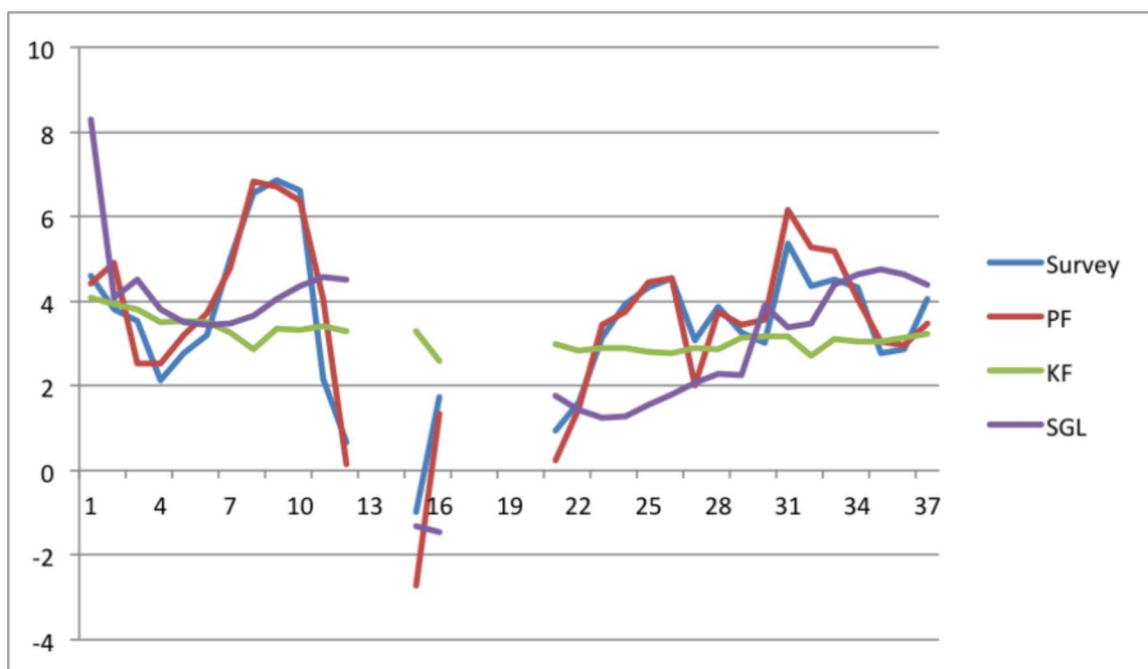


Figure 1.4: Paths of output growth expectations, Mexico

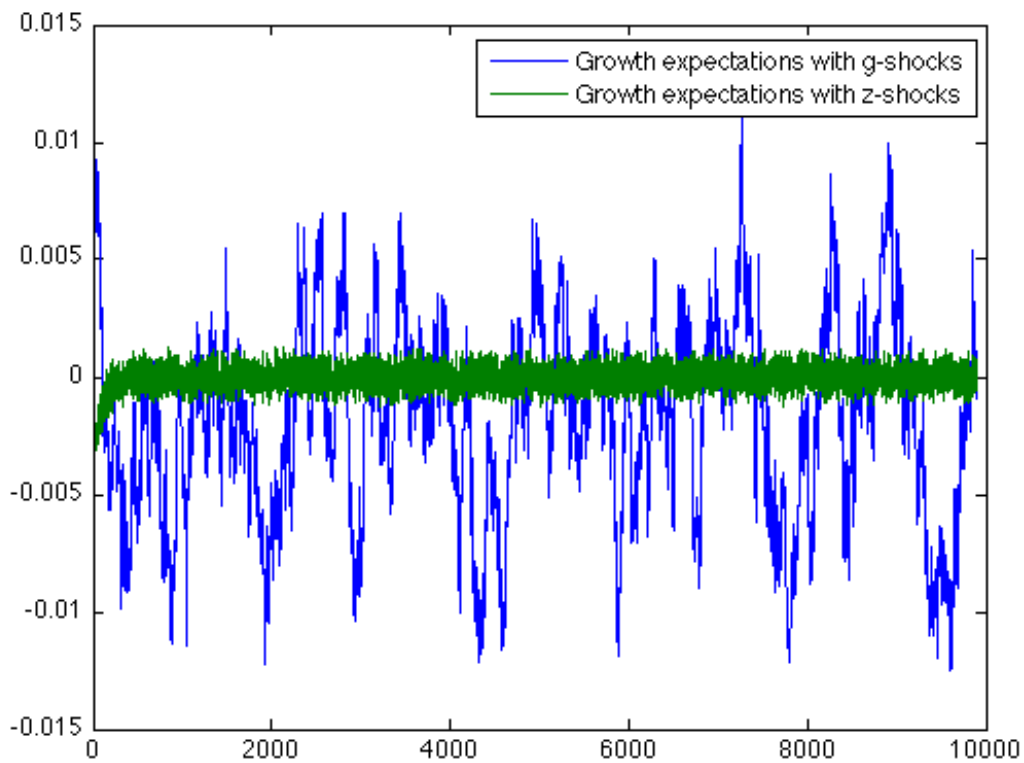


Figure 1.5: Output growth expectations with SGL

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Chapter 2

Financial reforms and financial instability

2.1 Introduction

In the first chapter I showed that the failures to identify output trends constitute a quantitatively important factor for the occurrence of overborrowing crises, especially in emerging economies. In this chapter we analyze a kind of economic phenomenon that, by changing the economic structure, leads to the necessity of redefinition of output trends: Financial reforms.

We study the relationship between different types of financial reforms and financial instability, measured as the frequency of banking crises. We document the following facts:

1. Financial liberalizations are associated with a higher frequency of banking crises.

This regularity is stronger in emerging economies than in advanced economies.

2. The increase in financial turbulence is mainly concentrated within a time-window of five years after the reforms. If a country does not experience a banking crisis within that period, the probability of experiencing a crisis afterwards becomes significantly smaller.
3. Financial liberalizations increase the probability of bifurcation paths: Some countries experience actual permanent increases in productivity after financial liberalizations and hence do not suffer financial crises, while others only experience transitory increases in productivity and suffer financial crises in the years that follow the reforms as a consequence of overspending with respect to what the actual realizations of productivity would have implied as optimal behavior.
4. Liberalizations of capital accounts, securities markets, interest rates, and barriers to entry, all contribute positively to a higher frequency of banking crises.

The above regularities are explained by two theoretical mechanisms that interact with each other. The first mechanism is the problem of identification of productivity trends, as established in chapter 1. The reforms imply a change in the structure of the economy, such that information prior to the reforms becomes obsolete as an input for forming expectations on permanent income. If the reforms are followed by good times, agents may update their expectations in a positive direction. According to the permanent income hypothesis, this should lead to more borrowing. If after some time those expected increases in productivity are not validated, agents may face difficulties to honor their financial obligations, increasing the likelihood of a financial crisis. As a byproduct of the learning-the-productivity-trends process, the variance of expected permanent income tends to be higher after the reforms, which, as it was analyzed in chapter 1, is associated with a higher likelihood of crises as a product of overborrowing.

The second mechanism is related to informational problems. It is a well established

fact that the supply of international credit is procyclical, especially more for emerging economies. This fact can be explained by models of imperfect information that lead to procyclical informational capital (see Stiglitz, 2000). Financial liberalizations, by facilitating the inflow and outflow of short-term capital flows, accelerate economic fluctuations, hence turning informational capital more procyclical, what is conducive to more financial instability. This effect is stronger in emerging economies, where the institutions that are supposed to mitigate informational problems are weaker.

The fact that the increase in financial instability that follows financial liberalizations is mainly concentrated in the short-run can also be explained by the two above described theoretical mechanisms. Suppose that a reform is associated with an expectation of higher permanent income (an assumption that seems natural for the reforms to be considered as socially desirable). Then, we should observe an increase in current consumption as a response to the reform. The increase in consumption would have multiplier effects that would reinforce the expectations of higher output. Also, suppose that the reform implies a structural change in the process that determines the productivity of the economy, such that information previous to the reform is useless as a guide for expectations on future productivity. Suppose that in order to form expectations about future output growth, agents use the observations of current output growth to Bayesianly update beliefs (i.e., output growth observations are the signals the agent uses to update expectations). The impact of a signal of a given magnitude on beliefs will be greater the shorter the history of signals. Hence, large negative signals will have a bigger impact on financial instability in the short-term than in a longer term.

Regarding the mechanism related to informational problems, consider the following example. Suppose that an economy that was closed to short-term capital flows abandons mobility restrictions at time t . Before the liberalization, the economy did not

need to develop sophisticated informational systems to select and screen the recipients of capital flows. Thus, at the time of the reform the stock of informational capital will be small. If developing proper informational systems takes time (as in any learning-by-doing process), then the economy will be capable of developing those systems only gradually. Hence, the impact of a negative signal on financial instability would be greater early after the reforms than in a longer term.

Finally, imperfect information theory imply that the reforms that lead to liberalization of sectors that are more dependent on informational capital should have a bigger impact on financial instability. Fact 4 empirically supports this theoretical corollary.

2.1.1 Related literature

This chapter is related to at least three branches of literature.

The first branch focuses on the convenience of financial liberalization for economic growth. McKinnon (1973) and Shaw (1973) are seminal papers in this field that triggered a vast empirical and theoretical literature. They claim that financial liberalization is good for economic growth. The argument states that financial repression prevents an efficient allocation of capital, and that financial liberalization, by unifying domestic capital markets, would boost financial development and economic growth. This approach does not contemplate the consequences of running a financial liberalization experiment in an economy with imperfect information. As Greenwald and Stiglitz (1986) show, matters are different under imperfect information. This chapter addresses some of the implications of considering markets with imperfect information, focusing on financial instability instead of on economic growth.

The second branch focuses on how the difficulties for identifying productivity trends

can lead to macroeconomic instability and overborrowing crises. Chapter 1, besides contributing directly to this literature, also offers a survey of it (see also Heymann and Sanguinetti (1998), Galiani et al (2002)). As explained in the introduction of this chapter, a corollary of this theory is that financial liberalization should increase financial instability, but if it does not, then it should lead to permanently higher levels of consumption. I empirically show the validity of this corollary. An empirical related antecedent to this branch is Mendoza and Terrones (2008), who found that 33 (22) percent of credit booms observed in the 1965-2006 period in developed (emerging) economies occurred after periods of large financial reforms.

The third branch is constituted by the empirical literature on financial liberalization, financial instability, and economic growth. I distinguish two contributions as the closest empirical antecedents to this paper. One of them is Loayza and Ranciere (2006), who estimate a model of short-run and long-run effects of financial intermediation on economic growth. I also pursue an analysis of short-run and long-run effects, but of financial liberalization on financial instability. The other contribution is Demirguc-Kant and Detragiache (1999), who also analyze the relationship between financial liberalization and financial instability. My analysis differs from their analysis in two dimensions. First, instead of using a dummy variable for measuring financial liberalization, as they do, I use an index that is built using seven dimensions of financial freedom –described in the next section. This measure has, by construction, higher variability. Second, they do not analyze three of the phenomena I address: short-run versus long-run effects, bifurcation of consumption paths after reforms, and the relationship between financial reforms and financial instability for specific types of reforms.

We also benefit from the empirical literature on banking crises that provides comprehensive datasets on banking crises, and from Abiad et al (2010), who present a

dataset on financial reforms that is a key input for my study. I describe the data in the next section.

2.2 Description of the data

We measure financial instability as the frequency of banking crises. We use data on banking crises from Laeven and Valencia (2008), who extend the database by Caprio et al. (2005). The database covers the universe of systemic banking crises for the period 1970-2007. The 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 financial institutions and corporations face great difficulties repaying contracts on time. Unlike prior work (Caprio and Klingebiel, 1996, and Caprio, Klingebiel, Laeven, and Noguera, 2005), they exclude banking system distress events that affected isolated banks but were not systemic in nature. As a cross-check on the timing of each crisis, they examine whether the crisis year coincides with deposit runs, the introduction of a deposit freeze or blanket guarantee, or extensive liquidity support or bank interventions. They identify 124 systemic banking crises over the period 1970 to 2007.

To measure financial liberalizations, we use Abiad et al (2010) database on financial reforms, covering 91 economies over the period 1973-2005. They distinguish between seven different dimensions of financial sector policy, as follows:

- Credit controls and excessively high reserve requirements: The questions used to guide the coding of this dimension are the following: Are there minimum amounts of credit that must be channeled to certain sectors, or are there ceilings on credit to other sectors? Are directed credits required to carry subsidized

rates? Is there a ceiling on the overall rate of expansion of credit? How high are reserve requirements?

- Interest rate controls: Interest rates are considered fully liberalized when all ceilings, floors or bands are eliminated. To guide the coding of this dimension, they judge, for deposit and lending rates separately, whether interest rates are administratively set, including whether the government directly controls interest rates, or whether floors, ceilings, or interest rate bands exist.
- Entry barriers: To guide the coding of this dimension, they assess how the government restricts the entry into the financial system of new domestic banks or of other potential competitors, for example foreign banks or non-bank financial intermediaries.
- State ownership in the banking sector: In coding the database, they look at the share of banking sector assets controlled by state-owned banks. Thresholds of 50 percent, 25 percent and 10 percent are used to delineate the grades between full repression and full liberalization.
- Capital account restrictions: They use several existing measures of capital account openness that already exist, and that have a wider country coverage, which are surveyed in Edison et al. (2002).
- Prudential regulations and supervision of the banking sector: Of the seven dimensions, this is the only one where a greater degree of government intervention is coded as a reform. To code this dimension, they ask the following questions: Does a country adopt risk-based capital adequacy ratios based on the Basle I capital accord? Is the banking supervisory agency independent from the executive's influence and does it have sufficient legal power? Are certain financial institutions exempt from supervisory oversight? How effective are on-site and

off-site examinations of banks?

- Securities market policy: They code the different policies governments use to either restrict or encourage development of securities markets. These include the auctioning of government securities, establishment of debt and equity markets, and policies to encourage development of these markets, such as tax incentives or development of depository and settlement systems. They also include policies on the openness of securities markets to foreign investors.

Along each dimension, a country is given a final score on a graded scale from zero to three, with zero corresponding to the highest degree of repression and three indicating full liberalization. Reversals, such as the imposition of capital controls or interest rate controls, are recorded as shifts from a higher to a lower score. The seven dimensions of financial liberalization are aggregated to obtain a single liberalization index for each economy in each year. Since each of the seven components can take values between 0 and 3, the sum takes values between 0 and 21, ranging from full repression to full liberalization.

The index shows that financial reforms advanced substantially through much of the sample. Countries in all income groups and in all regions liberalized. Considering averages of group of countries, trends look smooth, but at the individual country level the reform process was typically characterized by long periods of no change in policy. That is, at the individual country level financial reforms are non-ordinary events.

2.3 The empirical analysis

We first show the results of the regressions that demonstrate the four facts stated in the introduction of this chapter (described as hypothesis 1 to 3 in this section)

with no control variables. The next section shows that these results are robust to the introduction of control variables pointed out in the literature of banking crises as determinants of financial instability.

Hypothesis 1: Financial liberalization is associated with greater financial instability, especially in emerging economies

The first hypothesis considers the relationship between the aggregate score of financial liberalization and financial instability.

Equations (2.3.1) to (2.3.3) describe the basic regressions. The endogenous variable $BC_{i;t+1,t+h}$ is a dummy that takes value 1 if country i experienced a banking crisis between years $t + 1$ and $t + h$, and 0 otherwise. I regress that variable in the level of the financial reforms index for country i in year t ($FRI_{i,t}$) and on its change between years $t - x$ and t ($\Delta FRI_{i;t-x,t}$). Equation (2.3.2) adds country-fixed effects to the regression, and equation (2.3.3) also adds annual dummies.

$$BC_{i;t+1,t+h} = a_0 + a_1 FRI_{i,t} + a_2 \Delta FRI_{i;t-x,t} + u_{i,t} \quad (2.3.1)$$

$$BC_{i;t+1,t+h} = a_0 + a_1 FRI_{i,t} + a_2 \Delta FRI_{i;t-x,t} + f_i + u_{i,t} \quad (2.3.2)$$

$$BC_{i;t+1,t+h} = a_0 + a_1 FRI_{i,t} + a_2 \Delta FRI_{i;t-x,t} + f_i + f_t + u_{i,t} \quad (2.3.3)$$

Note that the endogenous variable is dated after t while the regressors are dated before t . As far as crises cannot be anticipated, the endogeneity problem would be solved.¹

Table (2.1) shows the results from the regressions of the specifications (2.3.1) to (2.3.3)

¹An anticipated crisis would not be a crisis as it comes to be understood.

for two models: the linear regression model and the logit model. The results are for $h = 5$ and $x = 1$. We later analyze the consequences of modifying h to any other scalar from 6 to 10, and of modifying x to any other scalar from 2 to 5. The table contains three panels. The top panel shows the results of the regressions that include all the countries in the sample. The mid panel includes only the advanced economies. The bottom panel includes only the emerging Asian, transition, and Latin American and Caribbean economies (emerging economies henceforth).

In the pooled data regressions for the whole sample or the emerging economies sample, the level of financial freedom is negatively associated with the frequency of banking crises. This result indicates that those countries whose financial systems are less repressed have a lower likelihood of suffering a banking crisis. Previous literature (Levine 1997, 2005) has shown that more developed financial systems are conducive to higher economic growth. This result seems to go in the same direction.

The coefficient of main interest is a_2 , that is, the coefficient associated to the change in the index of financial reforms, what measures the depth of the financial liberalization. In any of the regressions that do not include annual dummies, the coefficient is positive and significant. These results support the hypothesis that financial liberalization increases financial instability within a period of five years post-reforms. The effect is stronger for the sample of emerging economies. In fact, the coefficient is not statistically significantly different from zero for the sample of advanced economies.

Including country-fixed effects in the logit regressions leads to two limitations (Wooldridge, 2010): it requires the exclusion of countries with no variability in the dependent variable (i.e. countries that did not experience crises over the sample), what can create an important selection bias; (ii) it makes impossible the calculation of marginal effects. However, table (2.1) shows that the results from the linear regression model are similar to those from the logit model. This equivalence can be demonstrated calculating

the marginal effects for an average year/country using the coefficients of column (4), that do not suffer from the above limitations. In the sample of emerging economies, for example, the marginal effect associated with the level of FRI is -0.007, and the associated with the change in FRI is 0.052, similar to the coefficients estimated by ordinary least squares.

Introducing the first controls: testing the existence of non-linear effects and the importance of previous crises

Do financial liberalizations affect financial instability in a non-linear way? Is it the case that financial liberalizations actually increase financial instability, or that banking crises trigger financial liberalizations and those countries that experienced recent instability are more prone to suffer a new crisis?

The regression model described in equation (2.3.4) addresses these issues. Non-linear effects are tested by introducing the square of the change in FRI . The variable $PC_{i,t-j}$ stands for previous crisis, and it takes value one if country i experienced a banking crisis in year $t - j$, and zero otherwise.

$$BC_{i;t+1,t+h} = a_0 + a_1 FRI_{i,t} + a_2 \Delta FRI_{i;t-x,t} + a_3 (\Delta FRI_{i;t-x,t})^2 + \sum_{j=0}^k b_j PC_{i,t-j} + u_{i,t} \quad (2.3.4)$$

Table 2 summarizes the results of the linear regression model and table (2.3) those of the logit model, in both cases with country-fixed effects, for the sample of emerging economies, $h = 5$, $x = 1$, and $k = 1$. Note that we only show the results for emerging economies. Having shown that the effects of financial liberalizations are stronger in

emerging economies, the rest of the paper focuses on this particular sample.

The introduction of previous crises variables does not alter the sign of the coefficients associated with the change in *FRI* in any of the cases (columns (2) and (4) in tables (2.2) and (2.3)). The sign of the coefficients of crisis in the year of the financial reforms or in the previous year are both negative and significant, what suggests that a banking crisis is less likely when another crisis occurred recently. Furthermore, tables (2.2) and (2.3) reveal that there are no non-linear effects associated with financial liberalizations.

In columns (5) and (6) of tables (2.2) and (2.3) , we separate the changes in *FRI* into positive (liberalizations) and negative (reversions). Our suspicion is that the coefficient associated with negative changes could be higher than the one associated with positive changes (meaning that a decrease in the degree of financial freedom would diminish financial instability by more than financial liberalization would increase it), due to the fact that crises tend to cause reversions (Abiad and Mody, 2005), and that the occurrence of a recent crisis makes the occurrence of a new crisis less likely. However, the p-value of the differences between these two coefficients is small enough to dismiss such concern.

Hypothesis 2: The increase in financial instability is mainly concentrated in the short-run

The results shown so far were for $h = 5$, that is, we reported the effect of financial reforms on the frequency of banking crises within a period of five years post-reforms. Are the effects the same for a longer term? This section answers this question. For space reasons, we only show the results for the linear regression model with country-fixed effects. The pattern of results is similar for the other specifications and for

different choices of x (table (2.5) shows the results for different values of x from 1 to 5 for the linear regression model with country-fixed effects).

Table (2.4) shows the regressions for every h from 5 to 10 for each sample. The coefficient on financial liberalization remains positive and significant for every $h > 5$ in the sample of emerging economies.

To distinguish between short-term and long-term effects (defining the long-term as the period after more than five years post-reforms), it is necessary to calculate the marginal effects of financial liberalization on financial instability for different values of h . However, the estimated coefficients are not directly comparable. When h increases, we lose observations: the sample of banking crises is shorter for h larger. The loss of observations tends to decrease the value of the marginal effects for larger h . To overcome this issue, we replicate the estimations for every h using a fixed sample size, with ending date in 1995. This sample is called balanced sample henceforth, while the sample that includes all the possible years is called unbalanced sample.

Figures (2.1) and (2.2) show the evolution of estimated coefficients for different horizons, for the unbalanced and balanced sample, respectively. From figure (2.2), we observe that the coefficient is increasingly positive until $h = 5$, when it reaches an steady value (in the unbalanced sample case the coefficient diminishes after $h = 5$ due to the loss of crises episodes). These results indicate that the effects of liberalizations on financial instability are especially concentrated in the short-run. The marginal increase in the frequency of banking crises is virtually zero more than five years after the reforms.

Hypothesis 3: Reforms in sectors that are more dependent on informational capital have the greater impact on financial instability

The previous analysis was performed aggregating the different types of financial reforms. This section analyzes the effects of every individual type of reform, for the seven dimensions of financial reforms described in the database. The goal is to assess whether the contribution to financial instability of the different types of reforms differs.

Although the different dimensions of the *FRI* are positively correlated, there is a considerable variance in those correlations. Table (2.6) shows the different correlations among the seven dimensions.

Table (2.7) shows the results of the linear regression model for the sample of emerging economies with country fixed-effects. We control for the existence of previous crises in the two years before the reforms, and we use the dimension of banking regulation and supervision as a control variable. Column (1) includes all together the seven dimensions of financial reforms, namely credit controls, interest rate controls, entry barriers, state ownership in the banking sector, capital account restrictions, prudential regulation and supervision of the banking sector, and securities market policy. Columns (2) to (7) includes each reform individually plus the banking regulation and supervision dimension which is included as a control.

In what follows, we focus on the coefficients associated with the changes in the different dimensions of financial reforms. When the reforms are included all together, only the coefficient of the liberalization of the interest rate remains significant at the one percent level. This result is not surprising: as table (2.6) suggests, it is possible that the presence of multicollinearity is implying this result.

The inclusion of each dimension separately reveals that every type of liberalization is positively and significantly associated with financial instability. Liberalizations of interest rate controls, entry barriers, and securities market policies are still significant at the 1 percent level. Liberalization of capital account restrictions is significant at the 5 percent level.

The next question that we intend to respond is the following: Are these results robust to the inclusion of control variables that have been considered in the literature on banking crises as important determinants of financial instability? Next section addresses this question.

2.4 Robustness

In this section we perform a thorough robustness analysis. We restrict the analysis to the sample of emerging economies. We show the results for the linear regression model with no country-fixed effects or annual dummies. The pattern of results obtained with this specification is similar to the ones obtained for the other specifications.

Description of control variables

We consider an extensive set of control variables that have been considered in the literature as important determinants of banking crises. This aside provides a description of those variables.

Shocks that adversely affect the economic performance of bank borrowers and whose impact cannot be reduced through diversification should be positively correlated with systemic banking crises. The shocks associated with banking sector problems high-

lighted by the literature include cyclical output downturns that can be captured by real GDP growth, terms of trade deteriorations, real short-term interest rate, and declines in asset prices such as equity and real estate (Gorton 1988, Caprio and Klingebiel 1996, Lindgren et al 1996, Kaminsky and Reinhart 1996).

Given banks' exposure to interest rate risk, a large increase in short-term interest rates is likely to be a major source of systemic banking sector problems. The increase in short-term interest rates may be due to various factors, such as an increase in the rate of inflation, a shift toward more restrictive monetary policy that raises real rates, an increase in international interest rates, the removal of interest rate controls owing to financial liberalization (Galbis 1993), or the need to defend the exchange rate against a speculative attack (Velasco 1987, Kaminsky and Reinhart 1996).

Currency mismatch is another source of banking fragility. If borrowers can borrow in external currency while receiving their income in local currency, foreign exchange risk is shifted onto borrowers, and unexpected devaluation would affect bank profitability negatively through an increase in nonperforming loans. Antecedents of banking problems derived from currency mismatches can be found in Chile in 1981 (Akerlof and Romer 1993), in Mexico in 1995 (Mishkin 1996), in the Nordic countries in the early 1990s (Drees and Pazarbasioglu 1995), in Turkey in 1994, and in Argentina in 2001, among others.

Deposit insurance can prevent the occurrence of bank runs. However, if the premiums do not fully reflect the riskiness of bank portfolios, then the presence of deposit insurance creates incentives for taking excessive risk, i.e., it increases moral hazard (Kane 1989). The opportunities for taking risk are decreasing in the level of financial repression. Thus, if financial liberalization takes place in countries with deposit insurance, and it is not accompanied by a well-designed and effective system of prudential regulation and supervision, then excessive risk taking on the part of bank

managers is possible, increasing the likelihood of a banking crisis. In summary, there is ambiguity in theory with respect to the sign of the correlation between existence of deposit insurance and frequency of banking crises.

In countries with liberalized banking sectors but with weak bank supervision and easy-to-circumvent legal remedies, looting behavior is more likely (Akerlof and Romer, 1993). Thus, a weak legal system that allows fraud to go unpunished increases the probability of a banking crisis.

Sudden withdrawals of bank deposits with similar effects to those of a bank run may also take place after periods of large inflows of foreign short-term capital. Such inflows, often driven by the combined effect of capital account liberalization and high domestic interest rates owing to inflation stabilization policies, result in an expansion of domestic credit (Khamis 1996, Galiani et al 2003). When foreign interest rates rise, domestic interest rates fall, or when confidence in the economy weakens, foreign investors quickly withdraw their funds, and the domestic banking system may become illiquid (Calvo et al 1994).

The real interest rate may also be considered as a proxy for financial liberalization, as Galbis (1993) found that liberalization process tends to lead to high real rates. In the task of trying to obtain a reasonable proxy measure of financial liberalization, Pill and Pradhan (1995) find that the variable that best captures the extent to which financial liberalization has progressed is the ratio of credit to the private sector to GDP. Another variable that can proxy the progress with financial liberalization is the change in real credit. Since case studies point to a number of episodes in which banking sector problems were preceded by strong credit growth, we include lags of this variable as controls.

Inflation is a potential explanatory variable because it is likely to be associated with

high nominal interest rates and because it may proxy macroeconomic mismanagement, which adversely affects the economy and the banking system through various channels.

The rate of depreciation of the exchange rate may be used to test the hypothesis that banking crises may be driven by excessive foreign exchange risk exposure either in the banking system itself or among bank borrowers.

To test whether systemic banking sector problems are related to sudden capital outflows in countries with an exchange rate peg, the ratio of M2 to foreign exchange reserves can be introduced in the regression. According to Calvo (1996), this ratio is a good predictor of a country's vulnerability to balance of payment crises.

The government surplus as a percentage of GDP represents the financing needs of the central government. This variable may matter for at least three reasons. First, governments with financing difficulties often postpone measures to strengthen banks' balance sheets (Lindgren et al 1996). Second, failure to control the budget deficit may be an obstacle to successful financial liberalization (McKinnon 1991). Frustrated attempts of financial liberalization can create problems for the banking system. Third, capital inflows plus a perception of permanent increments in productivity can lead to an expansion of public spending that ex-post might be non-sustainable, if policy-makers' expectations are not validated (Guzman 2009).

The effect of adverse macroeconomic circumstances on the likelihood of a banking crisis should be of a less magnitude in countries where the banking system is liquid. To capture liquidity, Demirguc-Kant and Detragiache (1998) use the ratio of bank cash and reserves to bank assets.

GDP per capita is also used as a proxy of institutional quality. Indexes of the quality of the legal system, of contract enforcement, and of the bureaucracy do the same job,

approximating opportunities for moral hazard.

Following Hardy and Pazarbasioglu (1998), we also introduce regional variables.

In summary, we include the following control variables, whose sources and statistics are described in table (2.8): Initial GDP per capita (corresponding to the year 1973), real GDP growth, inflation rate, depreciation rate of real exchange rate, depreciation rate of nominal exchange rate, cash surplus/deficit of central government as a percentage of GDP, private consumption growth, private investment growth, terms of trade index, change in domestic credit to private sector as a percentage of GDP, bank liquid reserves as a percentage of bank assets, real interest rate, strength of legal rights index, number of procedures to enforce a contract, money and quasi money (M2) as a percentage of total reserves, regional dummies, dummy for previous banking crisis, lending minus deposit real spread interest, dummy for countries with explicit deposit insurance, change in foreign liabilities of the banking system as a percentage of GDP, and change in deposit liabilities as a percentage of GDP. Some other relevant variables are not included due to lack of data.

Methodology

The inclusion of control variables turns the panel unbalanced. For some variables the number of available observations is greater than for others. If we run the regressions including all the controls together, we would lose many observations of banking crises and of financial reforms, and we would be adding too many variables. To overcome these issues, we perform a robustness analysis that relies on a strategy that combines elements from Levine and Renelt (1992) and Sala-i-Martin (1997), that consists in successively including different subsets of variables as controls.

Levine and Renelt (1992) analyze how robust are the conclusions from cross-country

growth regressions to small changes in the conditioning information set. They take all the variables that have been significant in growth cross-country regressions. Then, they take all the possible combinations of these controls that include up to three variables, and run a growth regression that includes a set of variables that are always included in growth regressions, the variable of interest (that is, the variable whose coefficient's significance is queried), and the subset of controls. The regression is run for every possible subset of controls formed with the combinations described, and the coefficient associated to the variable of interest is computed for every regression. Finally, they identify the highest and lowest values of that coefficient that cannot be rejected at the 0.05 significance level. Let those values be β_L and β_U , respectively. They define an interval bounded by $[\beta_L - 2\sigma, \beta_U + 2\sigma]$, where σ is the standard deviation of the coefficient. If the interval includes the zero, then that result is said to be fragile. Otherwise, it is said to be robust. Each control variable plays the role of the “variable of interest” once.

Sala-I-Martin (1997) shows that the above test is too strong for any variable to pass it. Specifically, if the distribution of the estimators of the variable of interest has some positive and some negative support, then one is bound to find one regression for which the estimated coefficient changes sign if enough regressions are run. Hence, he proposes an alternative test. Instead of focusing on the extreme values of the interval and concluding that the variable of interest is fragile if zero belongs to the interval, his test pays attention to the fraction of the density function that lies to each side of zero. If the coefficient is expected to be positive, then its degree of robustness is higher when the fraction of the density function that lies to the right of zero is higher.

Our methodology takes elements both from Levine and Renelt (1992) and Sala-i-Martin (1997). We take all the possible combinations of 3 variables out the 23 variables listed above. The number of combinations adds up to 1771. Given that

our panel is unbalanced, the number of observations for the regressions run is not independent of the combinations we take.

In 99.8 percent of the regressions we run, the coefficient on the ΔFRI is positive. Furthermore, the coefficient is significant in 87 per cent of those regressions, and it is not significant in the very few cases for which it is negative.

Figure (2.3) shows that the likelihood of the estimated coefficient being significant is increasing in the number of observations. Indeed, the only two cases for which the coefficient has the wrong sign are cases in which the number of observations is the minimum. Furthermore, all the coefficients become significant once the number of observations exceeds 600.

We claim that the loss of significance for our coefficient of interest is due to the low number of observations, and not due to the fact that the inclusion of variables for which the available time-series is shorter are the variables that indeed alter significantly the relationship between financial liberalization and frequency of banking crises. To assess the validity of our assertion, we perform an additional exercise. We run the regressions excluding the controls, but changing the number of observations. Specifically, we run a whole set of new regressions, in which we replicate the sample size of every regression run with controls, but this time we add no controls. That is, our strategy implies a continuous disposal of observations, in order to run 1771 regressions of equal sample size as the 1771 controlled regressions run above.

Figure (2.4) shows our findings. Unsurprisingly, the relationship between significance of coefficients and number of observations is still positive and strong, and in particular it displays the same pattern as the regressions with controls, suggesting that our results in the regressions with controls were robust.

We follow the same strategy for assessing the robustness of the regressions that include

one at a time the different dimensions of financial reforms. The results are summarized in figures (2.5) to (2.16). The regressions are also robust to the inclusion of controls.

In summary, the inclusion of controls does not invalidate our previous finding of a significant and robust positive relationship between financial liberalization and financial instability, either at the aggregate or individual level of reforms.

2.5 Conclusions

In an ideal competitive world with perfect information, rational expectations, and in which transfers can be implemented, liberalizing financial relationships should be welfare-enhancing. In a world with imperfect information, or in which identifying permanent income cannot be done as the rational expectations hypothesis implies, liberalizing financial relationships may be detrimental for the economy. In this respect, this chapter showed how certain kinds of financial liberalizations actually spurred financial instability, especially in emerging economies.

The relationship between financial reforms and financial instability still leaves open questions of key importance for designing correct and socially desirable economic policies: What kinds of liberalizations are good and which ones are bad? Can gradual liberalizations be welfare-enhancing? Can control to financial flows be welfare-enhancing under imperfect information? What kind of financial flows need more regulation? These issues are still relevant for the policy agenda of emerging economies.

2.6 Appendix: Tables and Figures

Table 2.1: Dependent variable: $BC_{t+1,t+5}$

	(1)	(2)	(3)	(4)	(5)	(6)
All countries						
FRI_t	-0.010 (7.65)***	-0.006 (3.35)***	-0.004 (1.06)	-0.072 (7.22)***	-0.047 (1.85)*	-0.003 (0.04)
$\Delta FRI_{t-1,t}$	0.035 (4.36)***	0.028 (3.75)***	0.014 (1.83)*	0.236 (4.89)***	0.198 (3.68)***	0.094 (1.43)
Observations	2,089	2,089	2,089	2,089	1,475	1,475
R2/ Pseudo R2	0.030	0.160	0.210	0.033	0.014	0.099
Advanced economies						
FRI_t	0.001 (1.02)	0.003 (1.65)	0.018 (4.81)***	0.028 (1.01)	0.063 (0.83)	1.646 (3.07)***
$\Delta FRI_{t-1,t}$	-0.005 (0.70)	-0.006 (0.80)	-0.021 (2.46)**	-0.124 (0.62)	-0.159 (0.80)	-0.867 (1.95)*
Observations	594	594	594	594	189	189
R2/ Pseudo R2	0.000	0.130	0.220	0.004	0.016	0.613
Emerging Asia, Transition Economies, Latin America and the Caribbean						
FRI_t	-0.007 (2.93)***	-0.003 (0.81)	-0.009 (1.33)	-0.040 (2.84)***	-0.015 (0.49)	-0.102 (1.27)
$\Delta FRI_{t-1,t}$	0.055 (4.76)***	0.052 (4.61)***	0.039 (3.27)***	0.285 (4.74)***	0.282 (4.23)***	0.243 (3.02)***
Observations	928	928	928	928	800	800
R2/ Pseudo R2	0.030	0.160	0.250	0.026	0.027	0.159

Notes: * significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust t-statistics in parenthesis.

(1) Linear regression

(2) Linear regression with country-fixed effects

(3) Linear regression with country-fixed effects and annual dummies

(4) Logit model

(5) Logit regression with country-fixed effects

(6) Logit regression with country-fixed effects and annual dummies

Table 2.2: Linear regressions with country-fixed-effects

Emerging Asia, Transition Economies, Latin America and the Caribbean						
	(1)	(2)	(3)	(4)	(5)	(6)
FRI_t	-0.003 (0.81)	0.000 (0.08)	-0.003 (0.90)	0.000 (0.04)	-0.003 (0.86)	0.000 (0.08)
$\Delta FRI_{t-1,t}$	0.052 (4.61)***	0.045 (4.23)***	0.063 (5.28)***	0.049 (4.04)***		
Square $\Delta FRI_{t-1,t}$			-0.004 (1.43)	-0.002 (0.51)		
$\Delta FRI_{t-1,t}$ (+ changes)					0.046 (3.37)***	0.045 (3.52)***
$\Delta FRI_{t-1,t}$ (- changes)					0.080 (3.80)***	0.045 (2.05)**
Crisis in t		-0.217 (6.01)***		-0.215 (5.93)***		-0.217 (5.96)***
Crisis in $t - 1$		-0.159 (4.35)***		-0.158 (4.33)***		-0.159 (4.35)***
Observations	928	928	928	928	928	928
R2	0.160	0.220	0.160	0.220	0.160	0.220
p-value of differences ⁺					0.196	0.997

+ : Refers to differences in coefficients of positive and negative changes in FRI .

Notes: * significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust t-statistics in parenthesis.

Table 2.3: Logit regressions with country-fixed-effects

Emerging Asia, Transition Economies, Latin America and the Caribbean						
	(1)	(2)	(3)	(4)	(5)	(6)
FRI_t	-0.015 (0.49)	0.016 (0.40)	-0.017 (0.56)	0.014 (0.34)	-0.016 (0.52)	0.015 (0.39)
$\Delta FRI_{t-1,t}$	0.282 (4.23)***	0.258 (3.00)***	0.397 (3.94)***	0.392 (2.85)***		
Square $\Delta FRI_{t-1,t}$			-0.036 (1.59)	-0.040 (1.30)		
$\Delta FRI_{t-1,t}$ (+ changes)					0.239 (2.98)***	0.237 (2.39)**
$\Delta FRI_{t-1,t}$ (- changes)					0.585 (2.23)**	0.429 (1.49)
Crisis in t		-1.831 (2.94)***		-1.827 (2.90)***		-1.815 (2.92)***
Crisis in $t - 1$		-1.235 (2.75)***		-1.251 (2.76)***		-1.235 (2.73)***
Observations	800	800	800	800	800	800
R2	0.027	0.122	0.030	0.125	0.029	0.123
p-value of differences ⁺					0.235	0.554

+ : Refers to differences in coefficients of positive and negative changes in FRI .

Notes: * significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust t-statistics in parenthesis.

Table 2.4: Short-term and long-term effects

	$BC_{t+1,t+5}$	$BC_{t+1,t+6}$	$BC_{t+1,t+7}$	$BC_{t+1,t+8}$	$BC_{t+1,t+9}$	$BC_{t+1,t+10}$
All countries						
FRI_t	-0.004 (2.37)**	-0.004 (2.36)**	-0.004 (2.23)**	-0.003 (1.61)	-0.001 (0.50)	0.000 (0.19)
$\Delta FRI_{t-1,t}$	0.025 (3.55)***	0.024 (3.25)***	0.020 (2.81)***	0.015 (1.99)**	0.007 (0.97)	0.008 (0.98)
Observations	2,089	2,000	1,911	1,822	1,733	1,644
R2	0.210	0.260	0.300	0.340	0.380	0.420
Advanced economies						
FRI_t	0.004 (2.34)**	0.005 (2.69)***	0.005 (2.80)***	0.006 (2.89)***	0.008 (3.16)***	0.008 (3.11)***
$\Delta FRI_{t-1,t}$	-0.008 (1.05)	0.007 (0.70)	0.009 (0.86)	0.010 (0.97)	0.005 (0.54)	0.004 (0.44)
Observations	594	572	550	528	506	484
R2	0.160	0.210	0.250	0.310	0.370	0.420
Emerging Asia, Transition Economies, Latin America and the Caribbean						
FRI_t	0.000 (0.08)	0.000 (0.15)	0.001 (0.26)	0.003 (0.69)	0.006 (1.28)	0.008 (1.51)
$\Delta FRI_{t-1,t}$	0.045 (4.23)***	0.041 (3.72)***	0.036 (3.38)***	0.031 (2.80)***	0.023 (1.96)*	0.025 (1.99)**
Observations	928	882	836	790	744	698
R2	0.220	0.270	0.300	0.330	0.350	0.370

Notes: * significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust t-statistics in parenthesis.

Table 2.5: Linear regression model with country-fixed effects, variable x

	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$
FRI_t	-0.004 (2.37)**	-0.005 (3.05)***	-0.006 (3.30)***	-0.006 (3.32)***	-0.006 (3.03)***
$\Delta FRI_{t-1,t}$	0.025 (3.55)***	0.018 (3.82)***	0.013 (3.54)***	0.010 (2.99)***	0.009 (2.61)***
Observations	2,089	2,000	1,911	1,822	1,733
R2/ Pseudo R2	0.210	0.230	0.240	0.260	0.280

Notes: * significant at the 10%, ** significant at the 5%, *** significant at the 1%. Robust t-statistics in parenthesis.

Table 2.6: Correlations

	CC_{t-1}	IRC_{t-1}	EB_{t-1}	SO_{t-1}	CAR_{t-1}	SMP_{t-1}	BRS_{t-1}
CC_{t-1}	1						
IRC_{t-1}	0.65	1					
EB_{t-1}	0.57	0.55	1				
SO_{t-1}	0.49	0.43	0.44	1			
CAR_{t-1}	0.59	0.60	0.51	0.52	1		
SMP_{t-1}	0.63	0.63	0.54	0.49	0.68	1	
BRS_{t-1}	0.61	0.59	0.56	0.49	0.58	0.64	1

Notes:

CC: Credit controls

IRC: Interest rate controls

EB: Entry barriers

SO: State ownership in the banking sector

CAR: Capital account restrictions

SMP: Securities market policies

BRS: Prudential Banking regulation and supervision

Table 2.7: Linear regression with country-fixed effects, dependent variable $BC_{t+1,t+5}$

	Emerging Asia, Transition Economies, Latin America and the Caribbean						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CC_{t-1}	-0.085 (3.61)***	0.014 (0.84)					
IRC_{t-1}	0.090 (4.50)***		0.073 (5.18)***				
EB_{t-1}	0.060 (2.48)**			0.081 (4.16)***			
SO_{t-1}	-0.011 (0.52)				0.025 (1.27)		
CAR_{t-1}	-0.012 (0.57)					0.035 (1.76)*	
SMP_{t-1}	0.020 (0.76)						0.069 (3.33)***
BRS_{t-1}	-0.165 (6.81)***	-0.112 (5.48)***	-0.167 (7.68)***	-0.165 (7.37)***	-0.118 (5.50)***	-0.123 (5.60)***	-0.152 (6.33)***
$\Delta CC_{t-1,t}$	-0.007 (0.17)	0.064 (1.69)*					
$\Delta IRC_{t-1,t}$	0.077 (3.05)***		0.082 (3.27)***				
$\Delta EB_{t-1,t}$	0.098 (2.37)**			0.118 (2.99)***			
$\Delta SO_{t-1,t}$	0.015 (0.52)				0.059 (2.18)**		
$\Delta CAR_{t-1,t}$	0.007 (0.23)					0.063 (2.28)**	
$\Delta SMP_{t-1,t}$	0.080 (1.81)*						0.133 (2.99)***
$\Delta BRS_{t-1,t}$	-0.053 (1.13)	0.004 (0.10)	-0.042 (0.93)	-0.036 (0.74)	0.001 (0.02)	-0.005 (0.11)	-0.021 (0.45)
Crisis in t	-0.287 (7.62)***	-0.246 (6.85)***	-0.275 (7.60)***	-0.273 (7.48)***	-0.232 (6.37)***	-0.248 (6.94)***	-0.253 (7.09)***
Crisis in $t - 1$	-0.173 (4.65)***	-0.146 (3.97)***	-0.159 (4.35)***	-0.151 (4.12)***	-0.142 (3.85)***	-0.141 (3.94)***	-0.151 (4.11)***
Observations	928	928	928	928	928	928	928
R2	0.27	0.22	0.25	0.24	0.22	0.23	0.24

Table 2.8: Control variables

Variable	Variability		Summary Statistics			
	Source		Mean	Std. Dev.	Min.	Max.
Initial GDP per capita (1973)	PWT	By country	5,245	3,224	640	15,089
Real GDP growth	WDI	By country & year	0.034	0.059	-0.449	0.165
Inflation rate	WDI	By country & year	0.994	5.837	-0.085	117.5
Depreciation rate of real exchange rate	PWT	By country & year	0.026	0.502	-0.812	13.21
Depreciation rate of nominal exchange rate	WDI	By country & year	1.531	10.51	-0.216	174.7
Cash surplus/deficit of central government as % of GDP	IFS & WDI	By country & year	-2.167	4.964	-41.22	16.11
Private consumption growth	PWT	By country & year	0.034	0.068	-0.306	0.469
Private investment growth	PWT	By country & year	0.033	0.958	-25.23	12.55
Terms of trade index (2000 = 100)	WDI	By country & year	109.6	31.82	50.98	306.6
Change in domestic credit to private sector as % of GDP	WDI	By country & year	0.399	9.175	-86.10	99.56
Bank liquid reserves as % of bank assets	WDI	By country & year	16.24	13.72	0.132	135.8
Real interest rate	WDI	By country & year	7.678	37.03	-97.81	789.8
Strength of legal rights index (0=weak to 10=strong)	WDI	By country	5.022	2.345	1	10
Procedures to enforce a contract (number)	WDI	By country	35.93	5.425	21	46
Money and quasi money (M2) as % of total reserves	WDI	By country & year	6.773	50.57	0	1,459.7
Dummy for Emerging Asian countries	Abiad et al (2010)	By country	0.474	0.474	0	1
Dummy for Latin American countries		By country	0.495	0.500	0	1
Dummy for Transition economies		By country	0.165	0.371	0	1
Dummy for previous banking crisis.	Laeven and Valencia (2008)	By country & year	0.458	0.498	0	1
Lending minus deposit real spread interest	WDI	By country & year	7.493	11.35	-20.48	114.0
Dummy for countries with explicit deposit insurance	Barth et al (2003)	By country	0.641	0.480	0	1
Change in foreign liabilities of the banking system as % of GDP	IFS	By country & year	-0.005	0.075	-0.839	0.340
Change in deposit liabilities as % of GDP	IFS	By country & year	0.009	0.101	-1.062	1.741

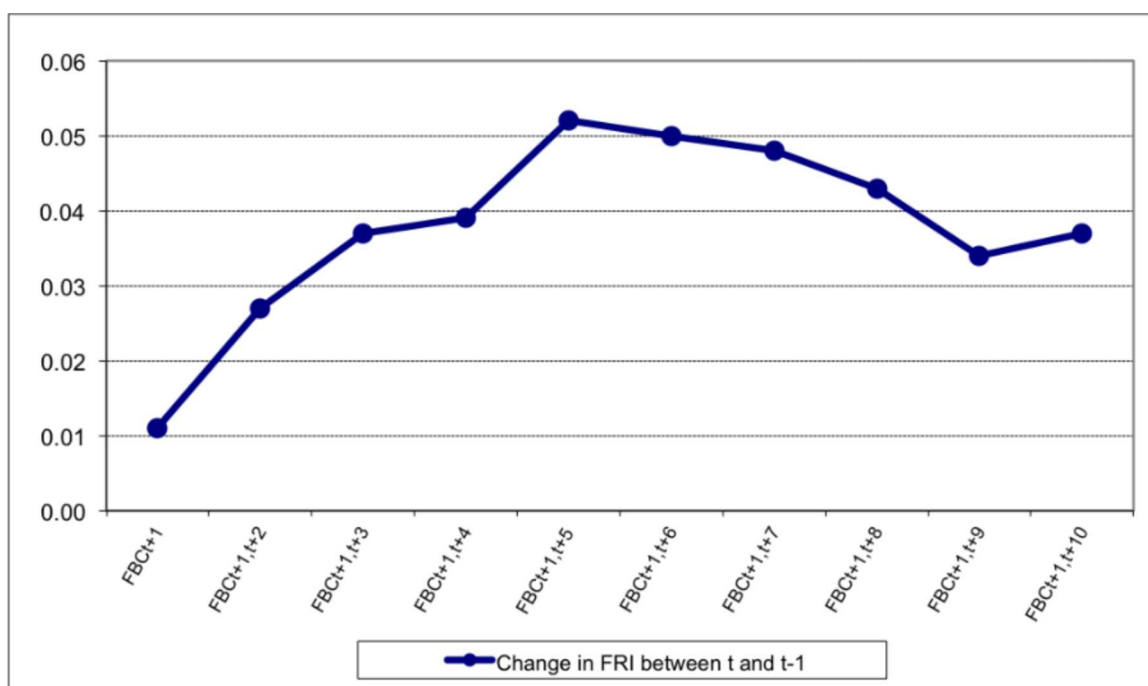


Figure 2.1: Effects of financial reforms on financial instability for different horizons, unbalanced sample

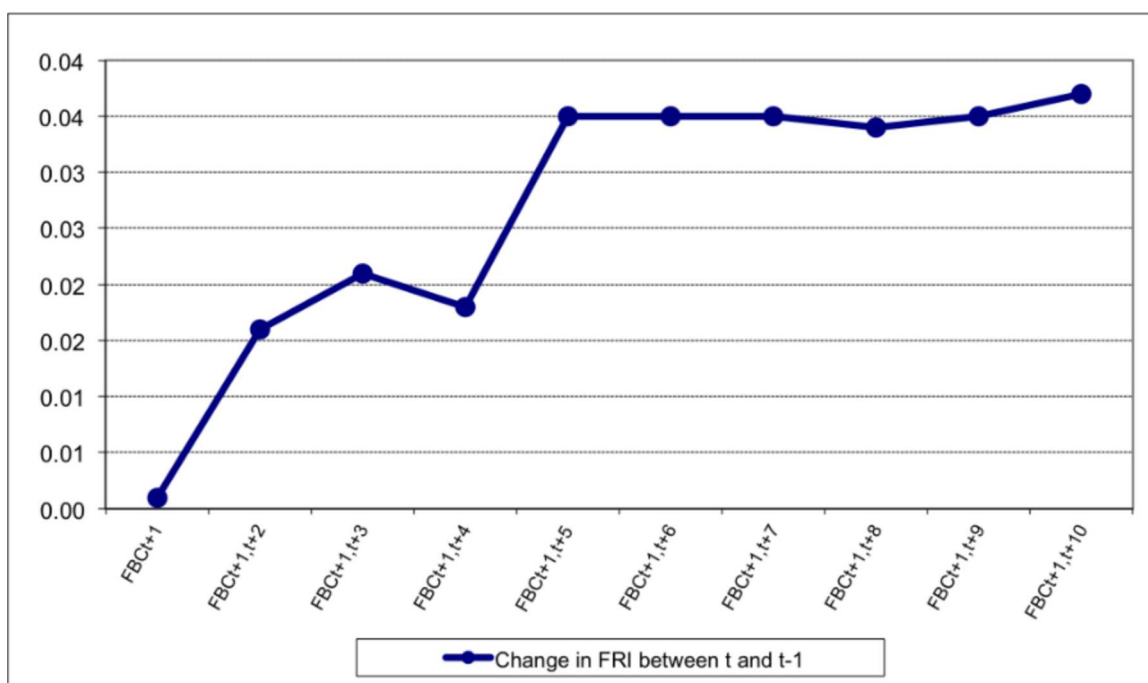


Figure 2.2: Effects of financial reforms on financial instability for different horizons, balanced sample

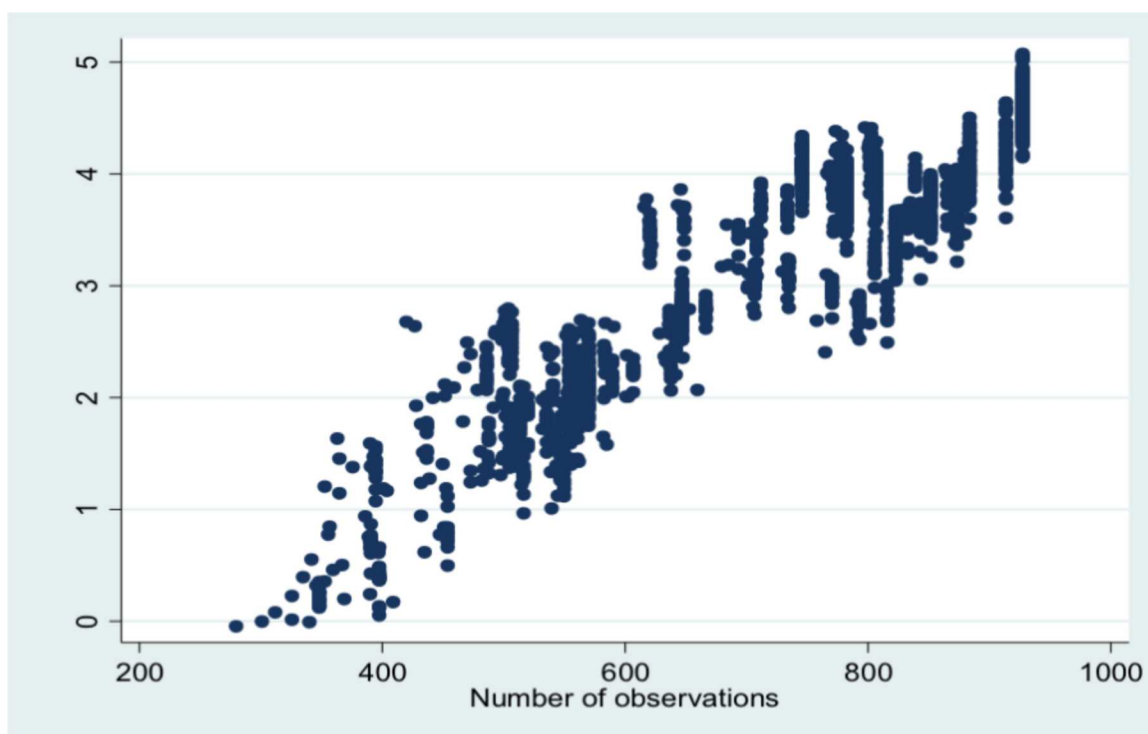


Figure 2.3: t-statistic and number of observations, with controls - Financial liberalizations

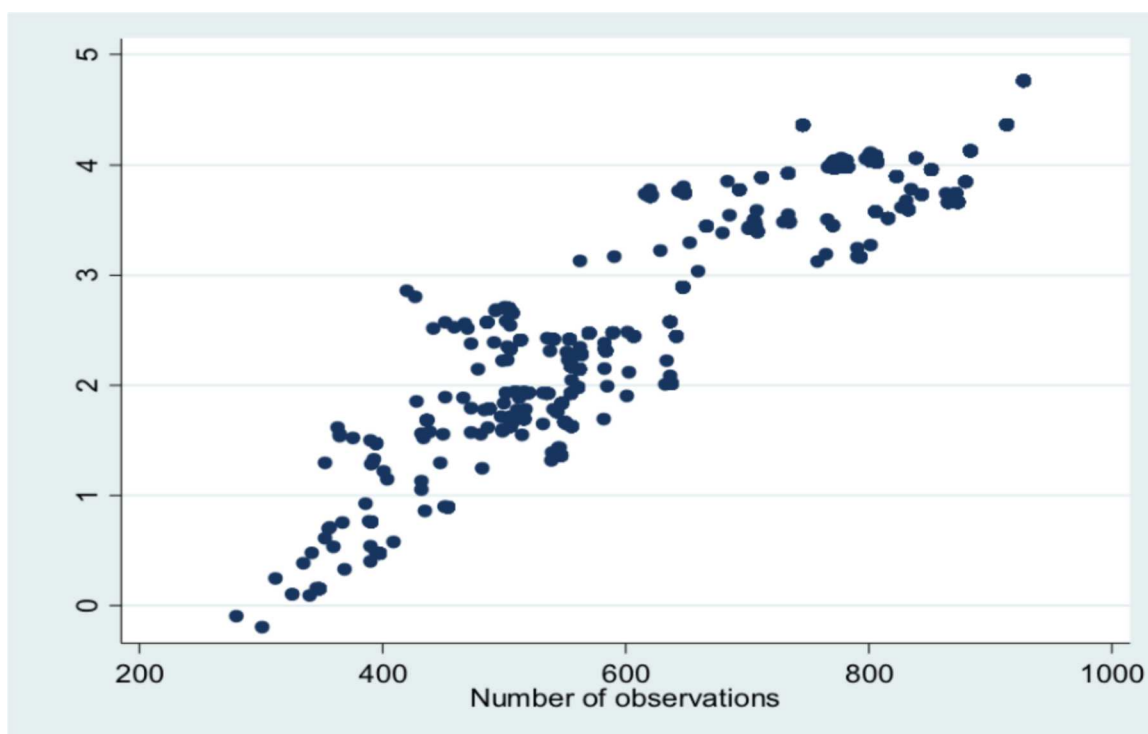


Figure 2.4: t-statistic and number of observations, with no controls - Financial liberalizations

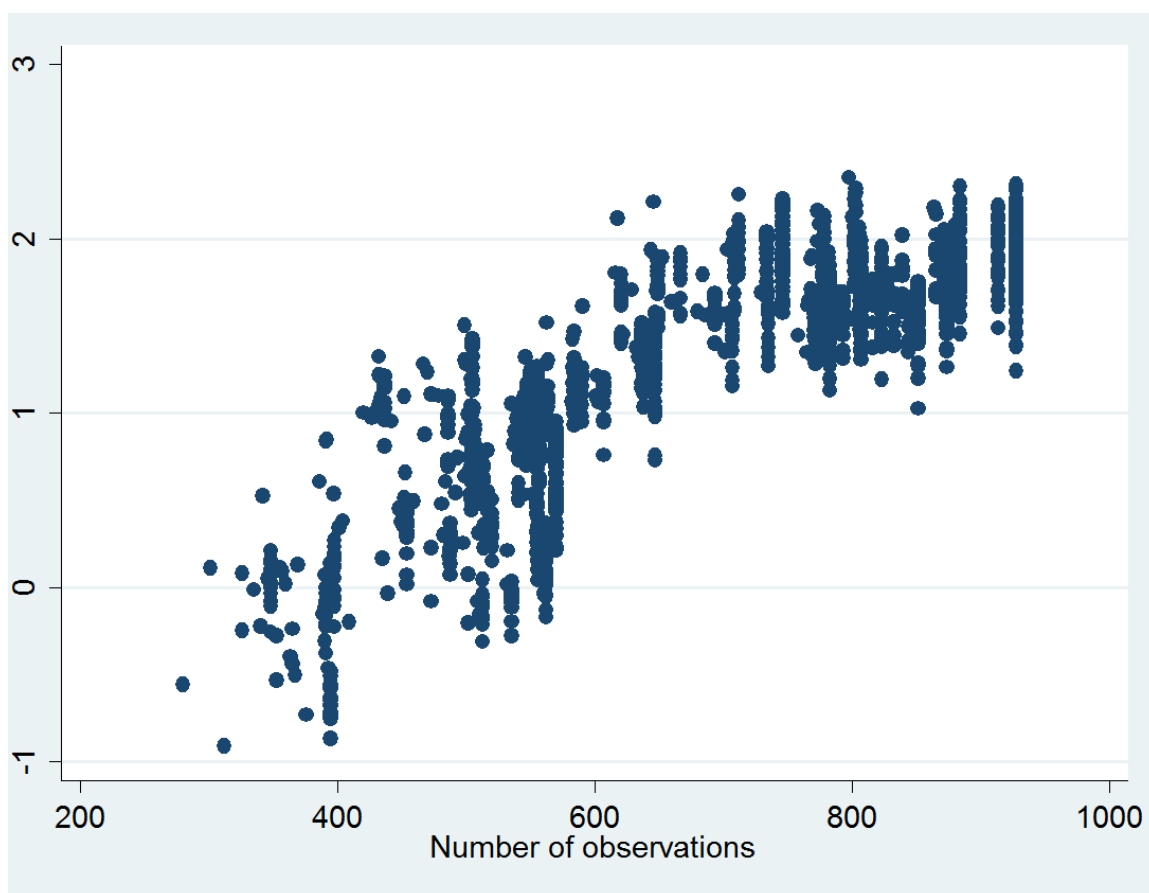


Figure 2.5: t-statistic and number of observations, with controls - Credit controls liberalizations

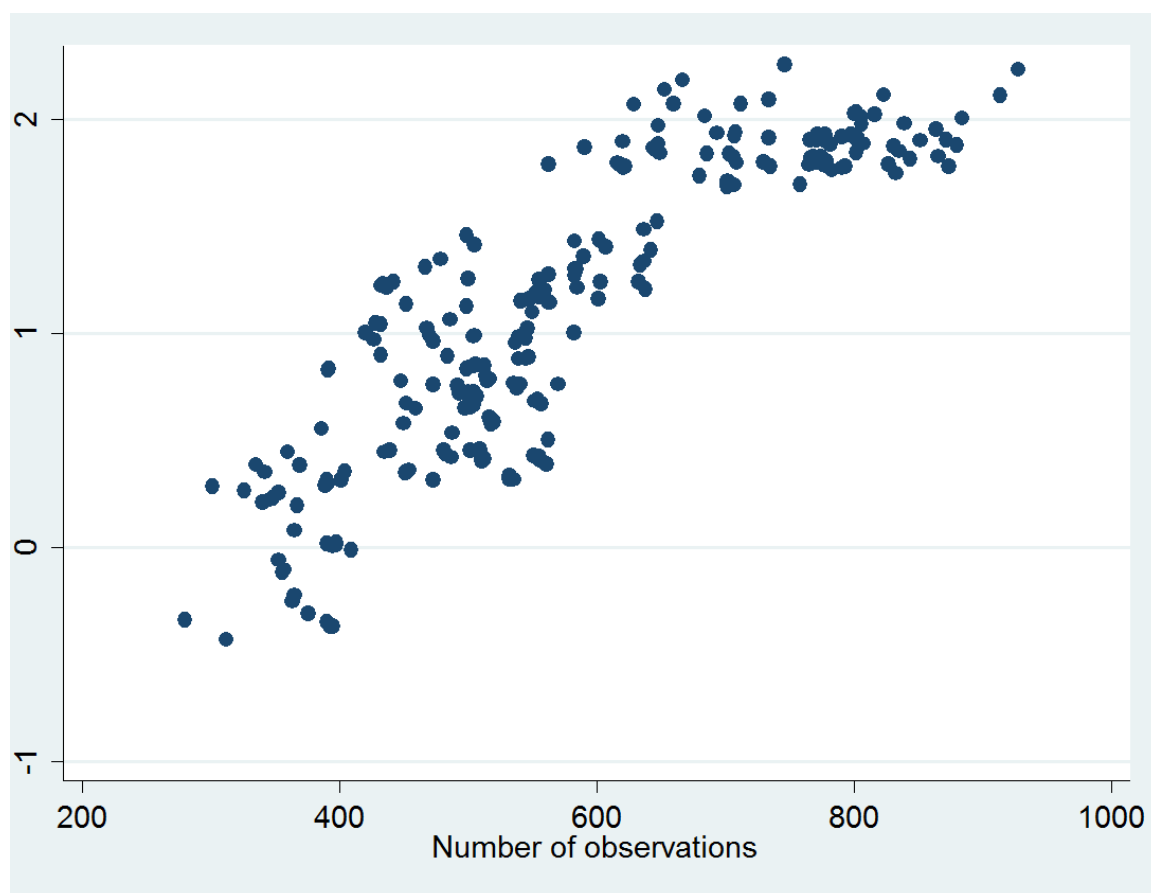


Figure 2.6: t-statistic and number of observations, with no controls - Credit controls liberalizations

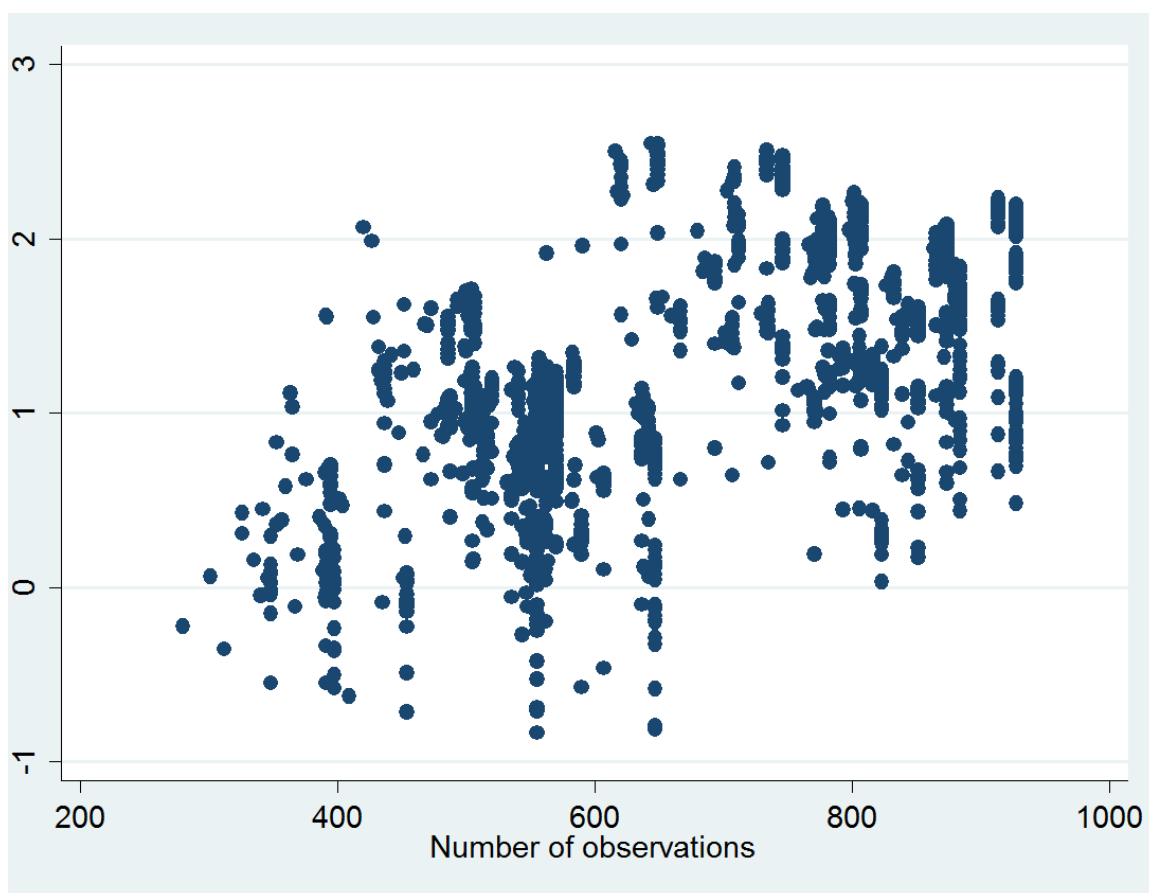


Figure 2.7: t-statistic and number of observations, with controls - Interest rate controls liberalizations

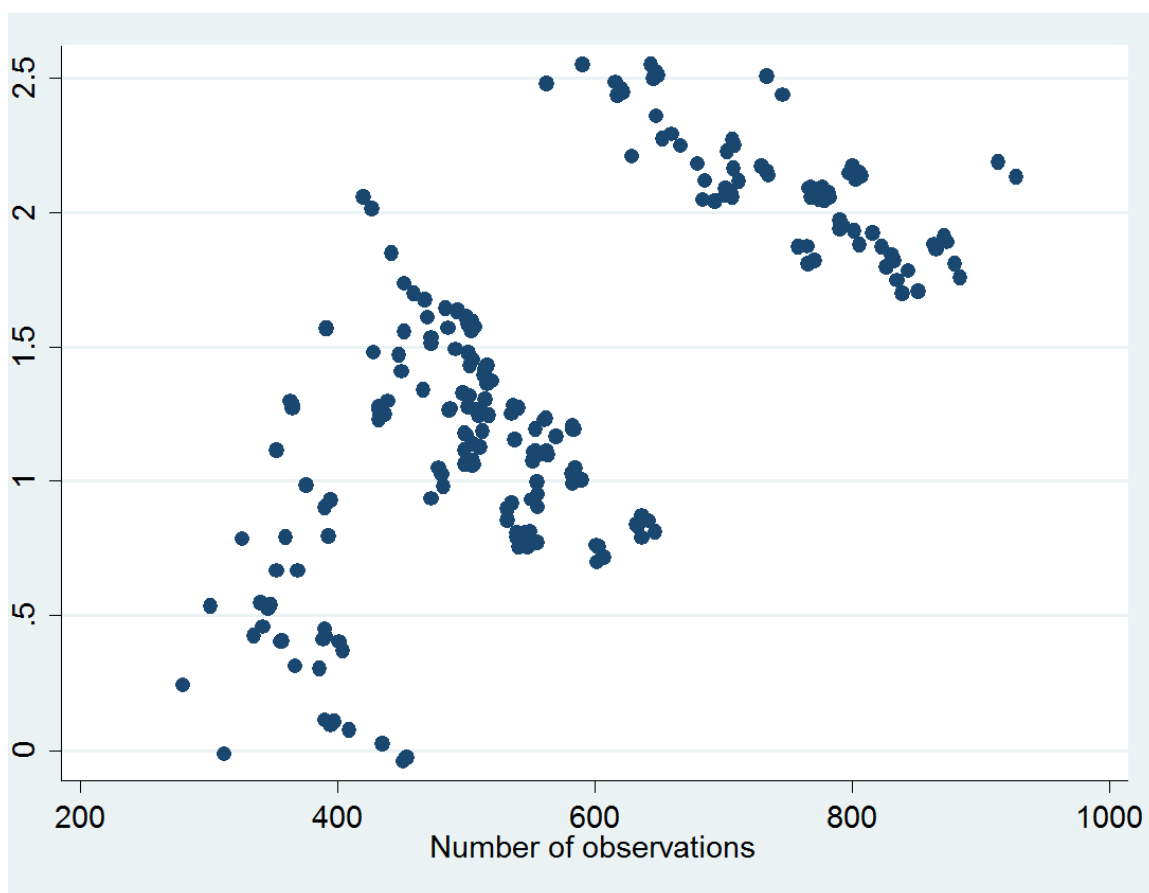


Figure 2.8: t-statistic and number of observations, with no controls - Interest rate controls liberalizations

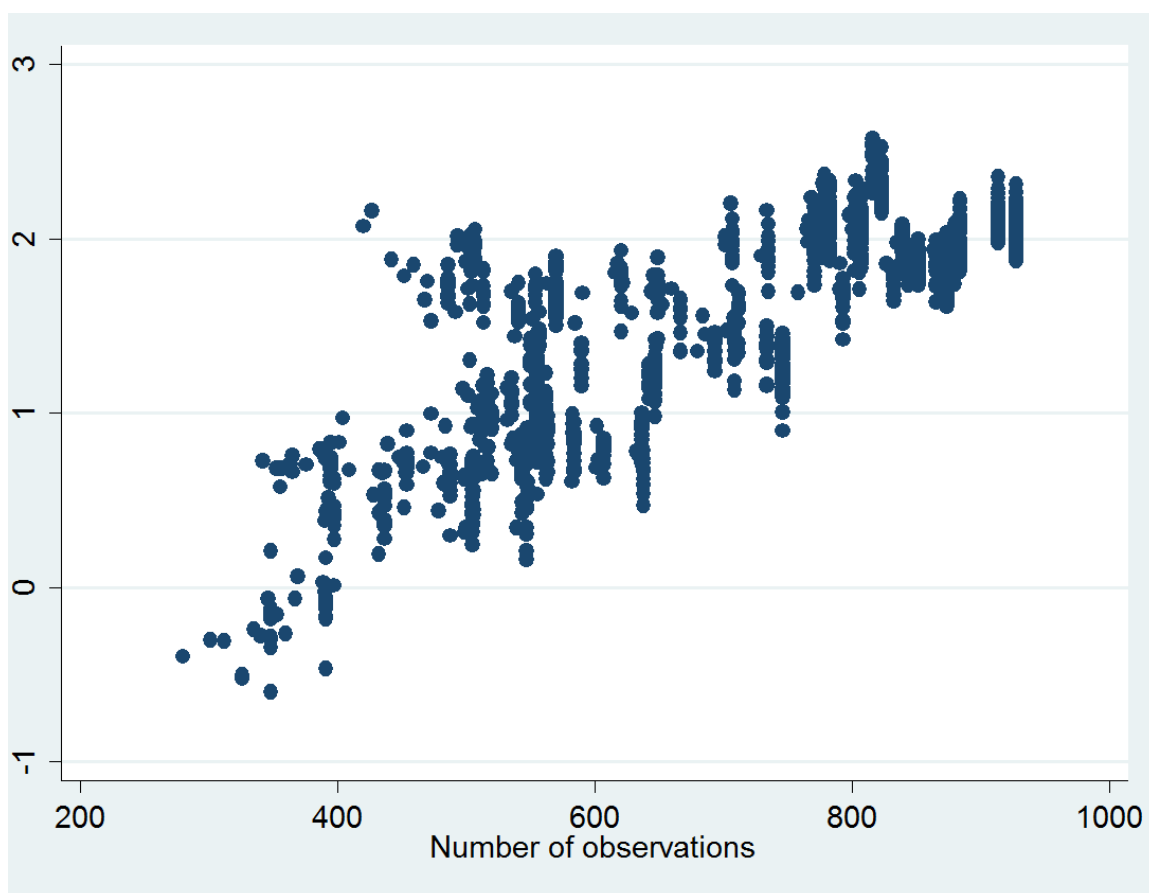


Figure 2.9: t-statistic and number of observations, with controls - Entry barriers liberalizations

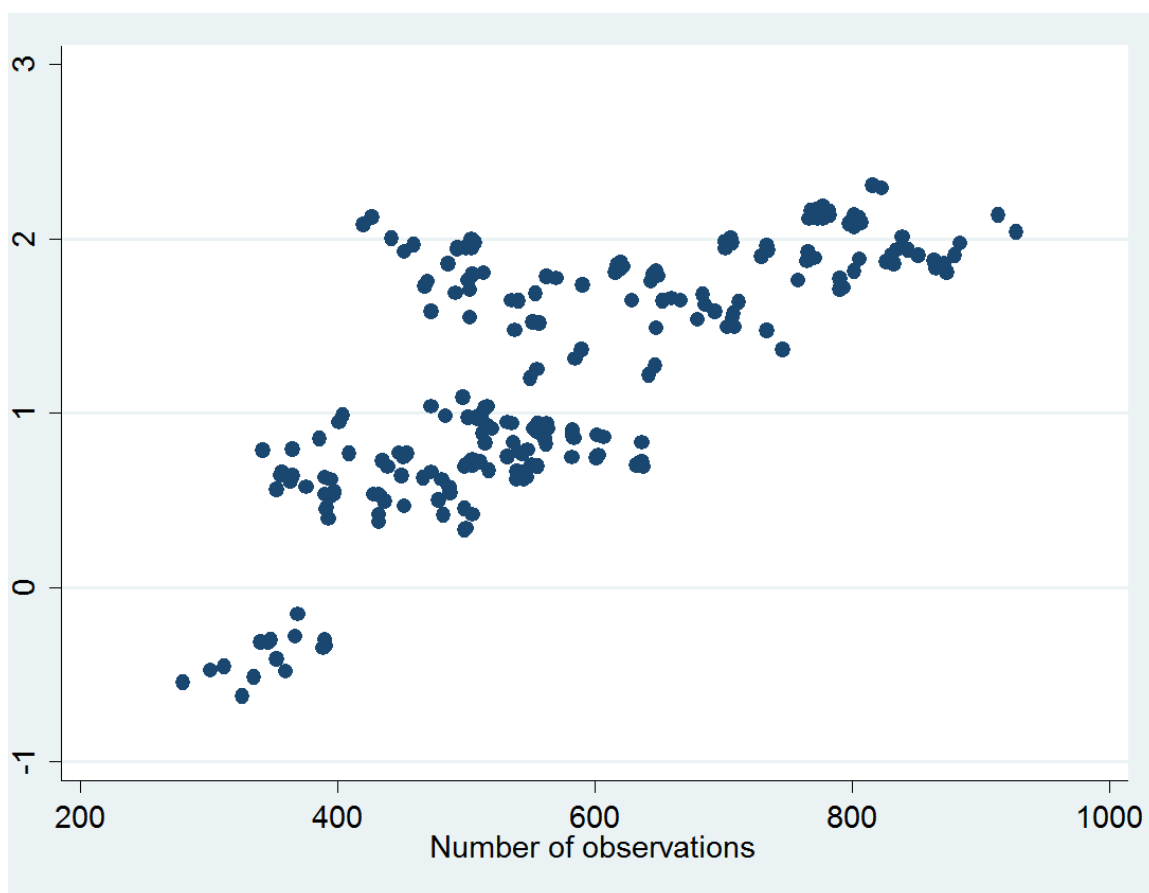


Figure 2.10: t-statistic and number of observations, with no controls - Entry barriers liberalizations

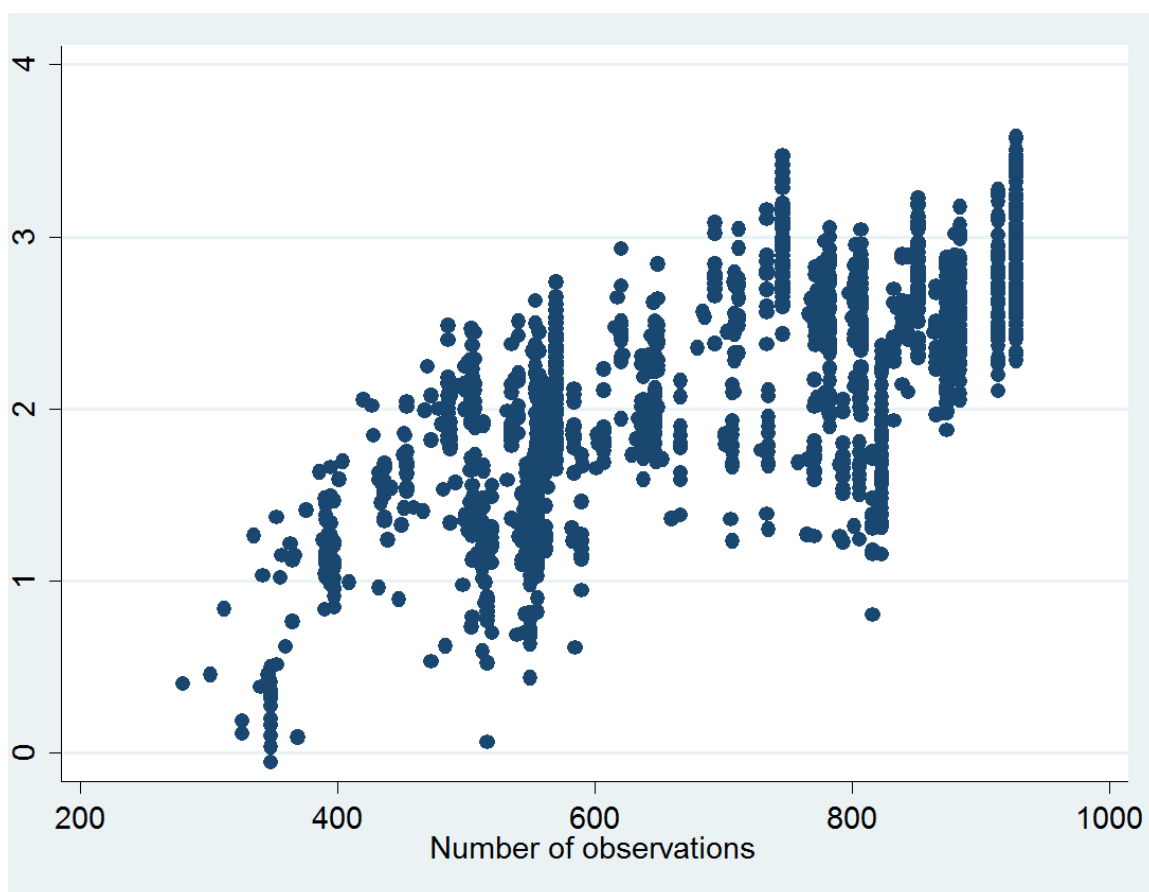


Figure 2.11: t-statistic and number of observations, with controls - State ownership in the banking sector liberalizations

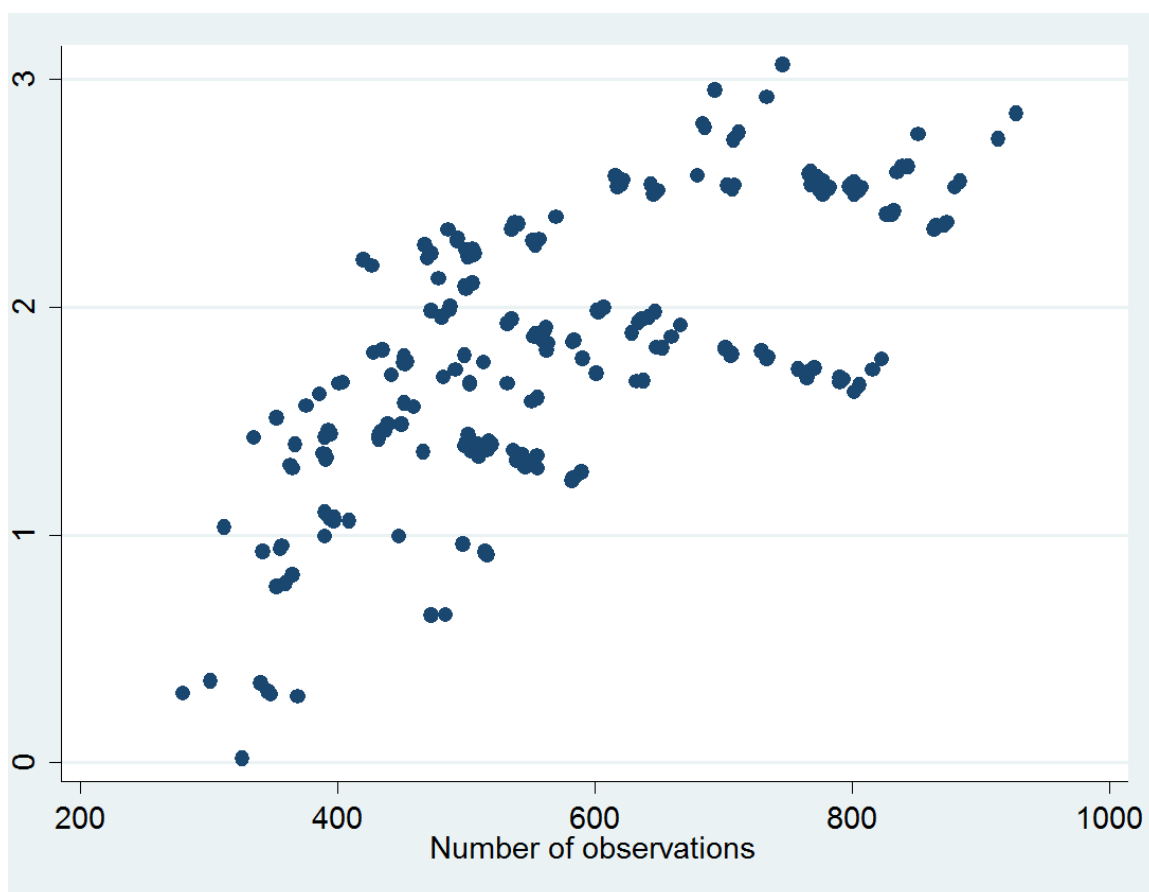


Figure 2.12: t-statistic and number of observations, with no controls - State ownership in the banking sector liberalizations

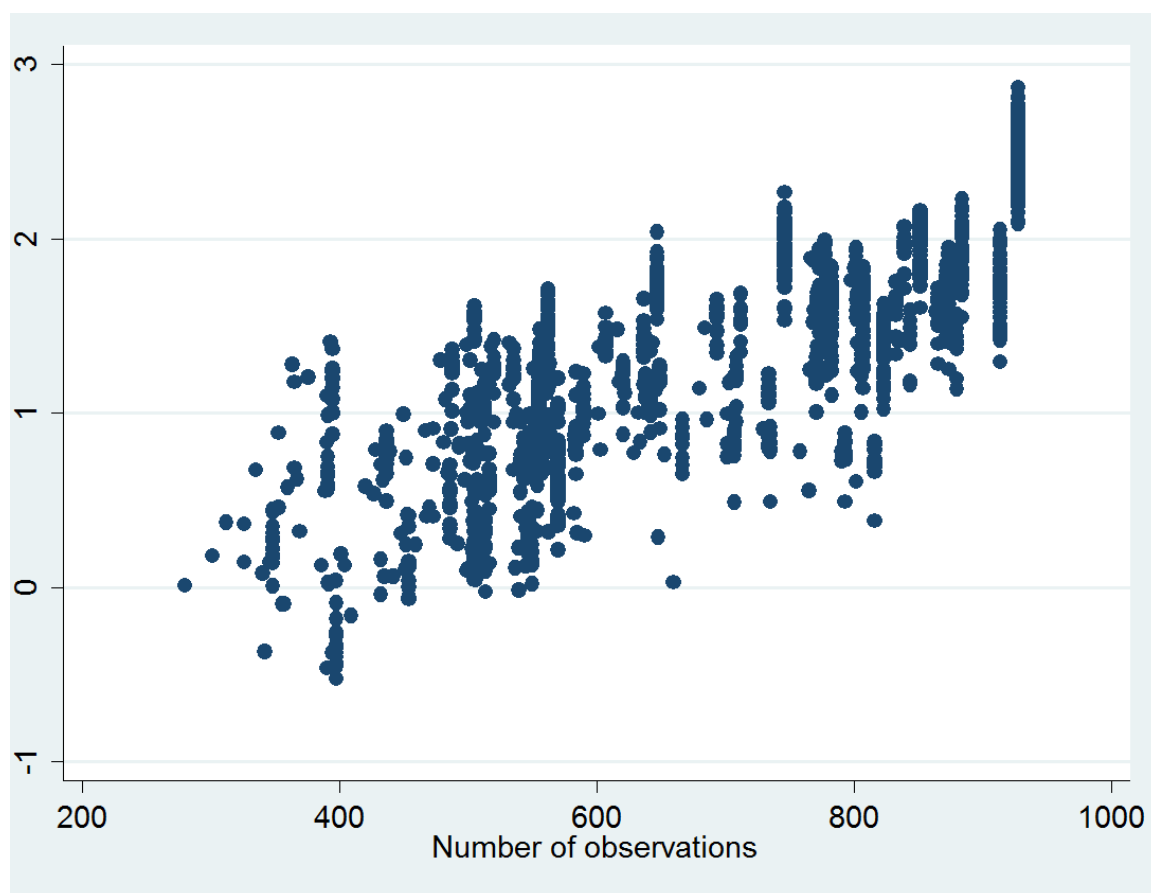


Figure 2.13: t-statistic and number of observations, with controls - Capital account liberalizations

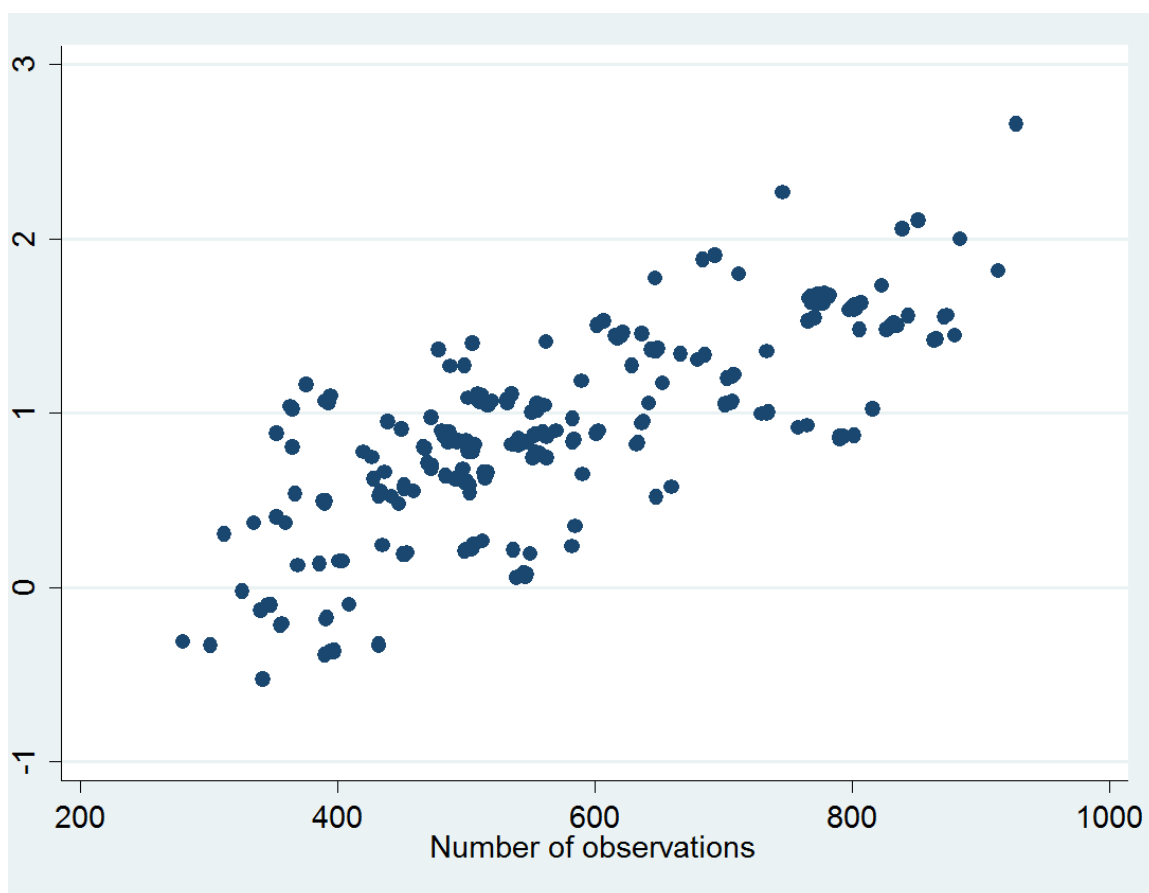


Figure 2.14: t-statistic and number of observations, with no controls - Capital account liberalizations

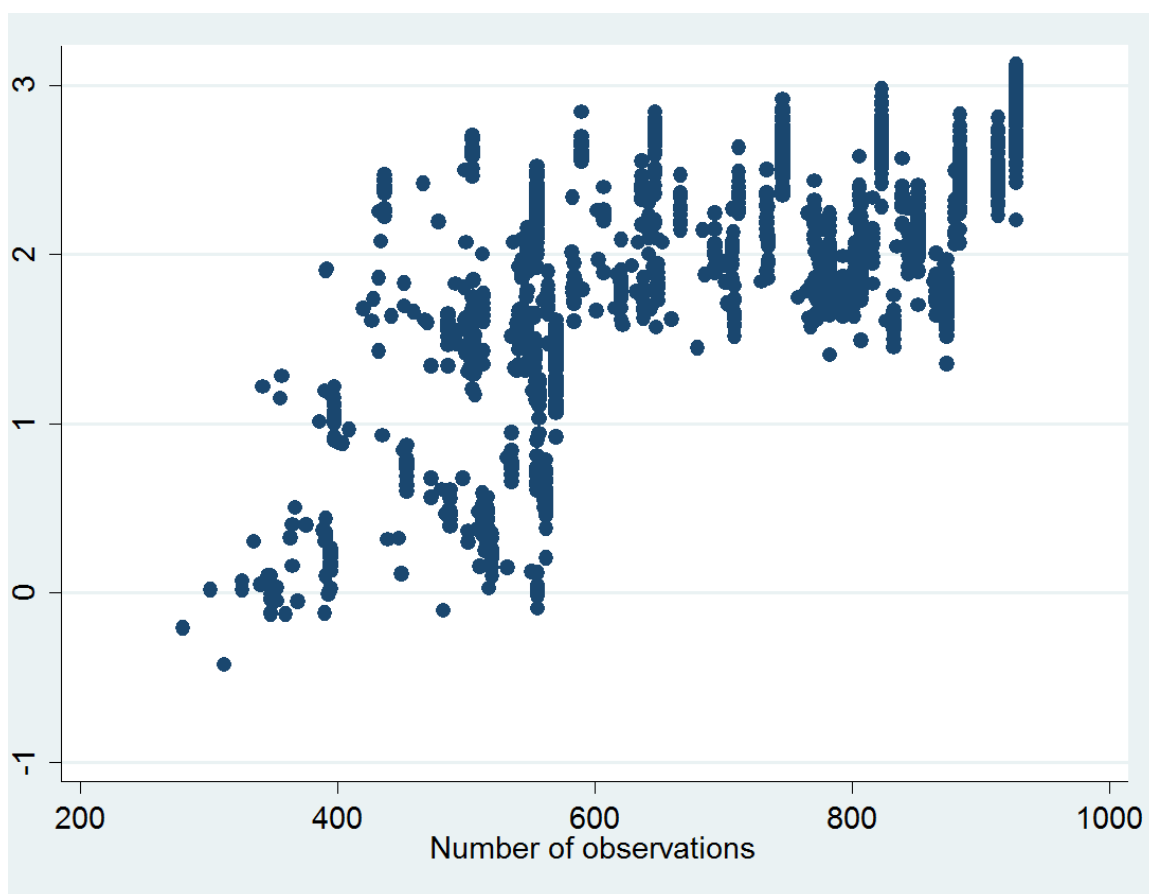


Figure 2.15: t-statistic and number of observations, with controls - Securities market policies liberalizations

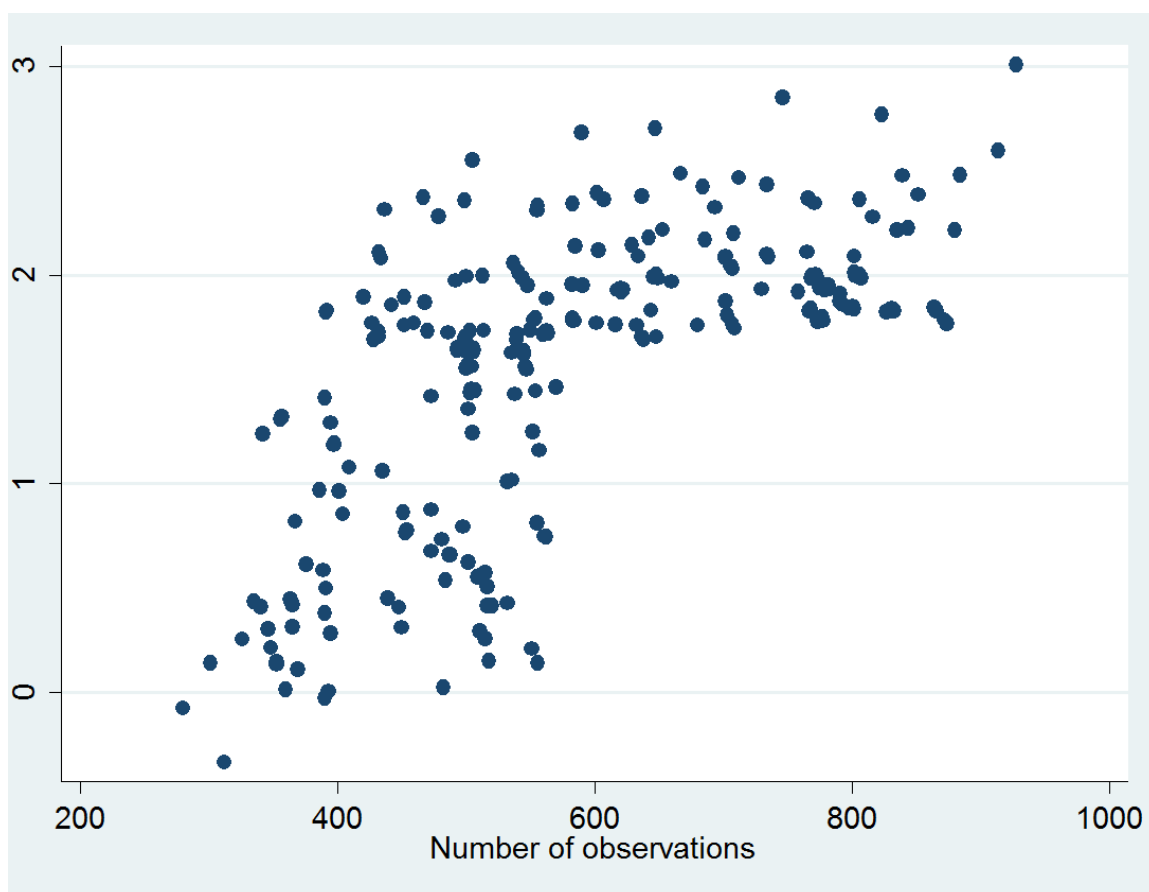


Figure 2.16: t-statistic and number of observations, with no controls - Securities market policies liberalizations

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Chapter 3

Stability of expectations and Severity of Crises

3.1 Introduction

This chapter analyzes the empirical validity of one of the corollaries of the so-called Minsky's Financial Instability Hypothesis (FIH), according to which the longer the span of time since the last crisis, 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 more stable the expectations, the more confident agents become about their own forecasts. The severity of a crisis is measured in dif-

ferent ways that seek to capture the output losses associated with crises. We describe the methodology for measuring severity of crises in section (3.2).

Our focus is on the type of financial crises that involve massive defaults, either in the private sector or in the public sector. As in chapter 1, we term these “overborrowing crises”, a term which denotes both banking and sovereign debt crises.

Consistent with the FIH, we find that overborrowing crises 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 long periods of stability.

3.1.1 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. 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. Howitt (2011) studies the interaction of expectations, leverage and a solvency constraint in a representative agent setup, and shows that adaptive learning about asset returns leads to periods of “cumulative optimism” followed by “cumulative pessimism”, what can lead to a crisis. Geanakoplos (2009) and Fostel and Geanakoplos (2008, 2012) introduce to the literature 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 understand the propagation of crises 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 switches in expectations from 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.

3.2 Data

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.

3.2.1 Crises and their severity

Dates of crises

The preliminary analysis we present in this paper uses the crises' panel cross-country 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.

Severity of crises

We estimate our model using four alternative measures of severity of crises.

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 loss is calculated as

$$Sev = \sum_{t=t_0}^{t_n} (\tilde{g}^y - g_t^y) \quad (3.2.1)$$

where Sev stands for severity of crisis, t_0 is the start date of the crisis, t_n is the end date of the crisis, \tilde{g}^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. IMF (1998) uses a three-year trend for calculating \tilde{g}^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 either Reinhart and Rogoff (2009) or Laeven and Valencia (2012). The end of the crisis is assigned to the year in which the GDP growth rate attains the pre-crisis GDP growth trend. This strategy for dating the crisis ending date may lead to overestimation of output 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.

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 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 five-year trend before the crisis and the GDP after the crisis.

The online appendix provides a database with all the measures of severity, Table (3.1) shows the correlations among the different measures. The measure calculated following the IMF methodology has the lowest correlation with the three others.

3.2.2 Expectations

We build series of expectations on GDP growth by using a learning algorithm for formation of expectations called stochastic-gain learning (SGL). This algorithm is introduced in the literature by Sargent (1993), and further explored by Marcet and Nicolini (2003) and Milani (2007) (see chapter 1 for a more extensive description of its use in the literature).

With SGL, agents follow a simple rule to form expectations about the future aggregate growth rate of output. 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 of the present. 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

$$E_t g_{t+1}^y = E_{t-1} g_t^y + \kappa_t (g_t^y - E_{t-1} g_t^y) \quad (3.2.2)$$

with

$$\kappa_t = \begin{cases} 1/t & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1} g_{t-s}^y|) < v_t^y \\ \kappa & \text{if } \frac{1}{S} \sum_{s=0}^S (|g_{t-s}^y - E_{t-s-1} g_{t-s}^y|) \geq v_t^y \end{cases} \quad (3.2.3)$$

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.

We provide a theoretical and an empirical reason for using SGL for building series of GDP growth expectations. The theoretical reason relies on Sargent (1993) and Marcet and Nicolini (2003). They present a series of conditions that a learning algorithm should satisfy to be a proper deviation from rational expectations. These conditions imply (i) asymptotic good forecasts (the so-called asymptotic rationality condition) and (ii) good forecasts along the transition (summarized in the so-called delta-epsilon criterion and internal consistency; see Marcet and Nicolini (2003) for a formal definition). SGL satisfies both sets of conditions.

The empirical reason addresses the question “What theoretical mechanism for formation of expectations has a better match with actual expectations?” To answer this question, we perform a comparison between three different mechanisms in terms of their accuracy for representing actual expectations on GDP growth taken from the Survey of Professional Forecasters (SPF) of Consensus Forecasts. These three mechanisms are perfect foresight, Kalman Filter learning (a mechanism that represents rational expectations under imperfect information), and the already introduced SGL. With perfect foresight, the expected growth rate of GDP is computed as the actual growth rate of GDP. With Kalman filter learning, the expected growth rate of GDP is a convex combination of prior beliefs and the observed GDP growth rate.

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, 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, stability

makes the learning processes not very different from the full information rational expectations approach.

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 every country. To construct this measure, we first compute the change in expectations from $t - 1$ to t , $CE_{t-1,t}$, for every period t :

$$CE_{t-1,t} = E_{t-1}g_t^y - E_tg_{t+1}^y \quad (3.2.4)$$

Then, we calculate a measure of stability of expectations between crisis($i-1$) and crisis(i), $SOE(i)$, as the average of the sum of changes in expectations between those crises:

$$SOE(i) = \frac{1}{t(i) - t(i-1)} \sum_{t=t(i-1)}^{t(i)} CE_{t-1,t} \quad (3.2.5)$$

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

Therefore, every period between two crises is associated with a different value of stability of expectations.

3.3 Empirical analysis

We perform our analysis of the relationship between severity of crises and stability of expectations analyzing different types of financial crises.

Our first set of regressions focuses only on overborrowing crises, defined as either systemic banking crises or 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:

$$Sev_i = \alpha + \beta SOE_i + \gamma X_i + \epsilon_i \quad (3.3.1)$$

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.

3.3.1 Results

Tables (3.2) to (3.8) show our results. Tables (3.2) to (3.7) use data on crises from Reinhart and Rogoff (2009). Table (3.8) 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 losses according to the IMF methodology, using a five-years trend for output growth. Column 3 assigns the Reinhart and Rogoff (tables (3.2) to (3.7)) or Laeven and Valencia (table (3.8)) 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 (3.2) reports the results with the inclusion of only overborrowing crises, for the pooled data analysis (42 countries, 100 episodes of crises with measures of severity in columns 3 to 5, but only 61 episodes with the IMF measure because the severity for those crises in which the GDP growth does not fall below the previous trend is not computed). The coefficient on stability of expectations is positive and statistically insignificant 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 those stable countries that after the crises transit to a permanently lower growth rate of output than in volatile countries that cross the previous GDP growth trend soon after the crisis. That measure is the least correlated with the other three measures. 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 (3.3) include country-fixed effects, and they display the same pattern of results.

In the regressions reported in tables (3.4) (pooled data) and (3.5) (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 in columns 3 to 5, only 129 with 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 an 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 coefficients and a loss of their significance. In this respect, table

6 shows that inflation and currency crises are more severe when the instability of expectations is greater. These results do not hold with the inclusion of country-fixed effects (table (3.7)).

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 due to the increased levels of uncertainty in the economy. This may lead to reversed causality: expectations of severe crisis might determine the value of the measure of stability of 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 (3.8) the results of regressions including a set of controls (55 emerging and advanced economies of which we use 54 due to the available data for controls, 156 episodes of crises with measures of severity in columns 3 to 5, 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. 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. Due to data availability we restrict our analysis to the crises episodes since 1970. We use Laeven and Valencia database, and we report the results only for overborrowing crises. The pattern of results still remains.

3.4 Conclusions

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. 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 more intense use of seigniorage and to more severe inflation and currency crises.

We conclude that, even though more volatile countries have more frequent overborrowing crises (as described in chapter 1), these crises are more severe when they follow long periods of stability.

3.5 Appendix: Tables

Table 3.1: 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 3.2: Pooled data, only overborrowing 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 3.3: Panel data, with country-fixed effects, only overborrowing 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 3.4: 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 3.5: 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 3.6: 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 3.7: 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 3.8: Pooled data, only overborrowing 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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