European University Institute

Department of Economics

Financial Factors, Rare Disasters and Macroeconomic Fluctuations

Bertrand Gruss

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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To my wife, María Paz

Introduction

The last two or three decades have been characterized by a strong phenomenon of financial globalization that has affected the sources and the transmission of business cycles around the world. First, there is overwhelming evidence that along this period global financial factors have played a key role in shaping macroeconomic fluctuation for several economies. The high volatility of capital flows towards emerging economies is a clear example. For instance, global financial factors played a key role in the reversal of capital flows to Latin America after a long cycle of indiscriminate inflows from the end of the 1980's to mid-1998: A partial debt default of a small country practically unconnected to the region as Russia resulted, via its effect on the balance sheet of international financial intermediaries, in a synchronized and widespread Sudden Stop in capital flows to the region, despite ample differences in economic performance and macroeconomic policies across countries (Calvo and Talvi 2005). The 1997 Asian crisis and the events related to the global financial crisis that hit the world in 2008 revealed that sudden shifts in financial conditions can also affect countries with an impeccable record of high growth and savings and countries with a highly developed domestic financial system: financial globalization has rendered virtually any economy vulnerable to systemic shocks originating in international financial markets. Second, it has became apparent that changes in financial conditions often entail a rare disaster pattern, in the spirit of Barro (2006). Episodes as the sudden stop associated with the Russian default or the liquidity crunch in the interbank market at the onset of the recent global financial crisis represent infrequent but extremely severe deteriorations in financial conditions.

This thesis attempts to shed light on the role of financial factors and vulnerabilities in shaping macroeconomic fluctuations. It contributes to the literature

that integrates financial factors into the real business cycle paradigm by introducing asymmetries and disaster risk in financial conditions, reflecting the low probability of sharp worsening in financial conditions that is found in data. The introduction of disaster risk in this thesis is done within a small open economy modeling framework. In this sense, while the trigger of disaster events is not endogenized, the emphasis is on exploring the role of financial frictions (such as working capital requirements or time-varying leverage) and of modeling features (e.g. variable capital utilization, the use of imported intermediate inputs, etc.) in affecting the propagation mechanisms when external conditions show a rare disaster pattern. In this sense, Chapter 1 analyzes the empirical pattern of external financial conditions for a sample of emerging economies and argues that a defining characteristic is the occasional disruption in access to foreign lending. The chapter presents evidence suggesting that these rare events in financial conditions relate to special features of their business fluctuations. It also shows that introducing these rare diasters in financial conditions in a canonical small open economy model has quantitatively important implications and makes emphasis on a careful specification of the exogenous processes in dynamic models for these economies. Chapter 2 assesses the contribution of the rare breakdowns in financial trade to macroeconomic fluctuations and shows that, indeed, Sudden Stops can account for the key empirical regularities of emerging market business cycles. This chapter also contributes to the literature by exploring the role of financial frictions and of modeling features, such as intermediate inputs and variable capital utilization, in the propagation mechanism of rare disaster shocks. Chapter 3 shifts the focus from the previous chapters to the specification of the financial friction. It explores the impact of cyclical swings in the tightness of financial frictions on asset prices and real variables. The chapter introduces a simple modification in a collateral constraint specification widely used in the literature. The modified friction, which is interpreted as the result of market imperfections at both ends of financial intermediation, reinforces the overreaction of asset prices to fundamental shocks and results in higher macroeconomic volatility, suggesting eventual gains from macro-prudential policies aimed at smoothing cyclical fluctuations in leverage requirements.

In more detail, Chapter 1 analyzes data on real interest rates from a sample of emerging economies and argues that the high volatility of their external financial conditions can be attributed to disaster events: infrequent but severe disruptions

in their access to foreign lending. The chapter proposes a regime switching model to capture the main characteristics of these rare events, including their severity, frequency and duration, and makes two distinctive points. First, Chapter 1 shows that introducing empirically motivated asymmetries in the process driving interest rates in a canonical small open economy model has quantitatively important implications for the probability distribution of its endogenous variables which, if ignored, can be quite consequential for calibration exercises. Also, the effects on the model's endogenous variables suggest that the regime switching nature of the shock leads to a weaker precautionary motive for savings which, to my knowledge, is a novel result. The quantitative exercises in this chapter highlight the relevance of a careful specification of the exogenous processes in dynamic models for emerging economies, taking due account of the nonlinearities they may face in their external conditions. Second, the chapter shows that the features captured by a nonlinear model for interest rates relate to well known stylized facts of business cycles in emerging markets. In particular, business fluctuations in countries displaying a clear asymmetric pattern in the distribution of their real interest rates show many of the characteristics that have been pointed out in the literature as typical of emerging economies.

Chapter 2 pursues the latter point further and relying on counterfactual exercises from a carefully calibrated extended model it shows that disaster events in financial trade can account for the empirical regularities of business fluctuations in emerging economies. Indeed, many emerging economies have experienced rare current account reversals followed by large declines in economic activity. These sudden stops are reflected in their real interest rates, which alternate between tranquil times, when the level is relatively low and stable, and crises, during which interest rates are higher and more volatile. In this chapter an estimated regime switching process of interest rates is embedded into a small open economy model with financial frictions. The model nests infrequent dramatic crises within regular business cycles, successfully matches the key second and higher order moments of the macroeconomic aggregates and produces plausible endogenous dynamics during crises. The chapter shows that the occurrence of sudden stops can account for the empirical regularities of emerging market business cycles: in counterfactual experiments in which sudden stops do not occur, business cycles resemble those of developed small open economies. Financial frictions are found to be essential for explaining emerging market fluctuations, but almost exclusively because of their

effects in crises.

Chapter 3 uses a dynamic small open economy model of business cycles with financial frictions to explore how macroeconomic fluctuations are amplified and transmitted across borders when frictions in financial intermediation entail procyclicality in credit conditions. I find that the procyclical behavior of lending standards amplifies shocks to fundamentals beyond the effect attributable to the financial accelerator mechanism. I interpret this extra amplification in the model as resulting from the interaction of financial constraints in the lending and in the borrowing side of financial intermediation. Asset prices play a crucial role in the propagation mechanism as procyclical lending standards reinforce their "overreaction" to shocks signaled by Aiyagari and Gertler (1999). Simulation results suggest the potential for sizeable stabilization gains from "macro-prudential" regulation aimed at containing the procyclical behavior of credit conditions.

Chapter 1

Rare Disasters in Emerging Market Financial Conditions

Abstract

Analyzing data on real interest rates from a sample of emerging economies this chapter argues that the high volatility of their external financial conditions can be attributed to disaster events: infrequent but severe disruptions in their access to foreign lending. I propose a regime switching model to capture the main characteristics of these rare events, including their severity, frequency and duration, and find that many features identified by this nonlinear model relate to key characteristics of business cycles in emerging markets. Finally, I show that introducing empirically motivated asymmetries in the process driving interest rates in a canonical small open economy model has quantitatively important implications for the probability distribution of its endogenous variables which, if ignored, can be quite consequential for calibration exercises. Overall, the results in this chapter highlight the relevance of a careful specification of the exogenous processes in dynamic models for emerging economies, taking due account of the nonlinearities they may face in their external conditions.

1.1 Introduction

Emerging economies and developing countries in general show higher macroeconomic volatility than developed economies, partly because they face large swings in external conditions, such as fluctuations in their terms of trade or in the cost of borrowing in international markets. As their export earnings typically rely on a narrow range of primary commodities or related manufacturing industries while they heavily depend on imported capital goods and intermediate inputs, they are vulnerable to high volatility in commodity prices. As they typically have a significant stock of foreign debt and rely on access to foreign credit to finance imports of intermediate inputs and capital goods, they are vulnerable to swings in the real interest rate they face in international markets. Many of these economies have opened significantly their capital accounts before developing their domestic financial sector. This makes them especially vulnerable to financial shocks resulting in large swings in capital inflows, driven by exogenous events that affect advanced economies, like changes in the world interest rate and shifts in international investors appetite towards risky assets in general–or towards emerging markets debt in particular. However, a notable feature of emerging economies is that an important fraction of the volatility in the external conditions faced by these countries is due to infrequent but extreme adverse realizations of shocks rather than repeated normal cyclical fluctuations. That is, they face "disaster" volatility in external conditions. Despite the extensive literature on the effects of the volatility of external conditions on emerging and developing economies, the rare disaster nature of these shocks has been largely unexplored. This chapter focuses on the rare disaster pattern displayed by one of the most relevant external conditions for emerging markets: financial conditions.

This chapter is structured in two parts. First, I analyze the time series of real interest rates in emerging economies showing that their high volatility can be attributed to disaster events: infrequent but severe disruptions in access to foreign lending. The inspection of higher order moments of interest rates series shows that occasional and large adverse realizations produce an asymmetric pattern for external conditions. I propose an empirical model to capture the main characteristics of these rare events, including their severity, frequency and duration, emphasizing the need to use nonlinear specifications. In particular, I provide evidence of regime-switching behavior of real interest rates suggesting that the access by

emerging economies to international borrowing is best characterized by a process alternating between a low level/low volatility regime and a high level/high volatility regime, the latter being a low-probability event in the line of a peso problem or a rare disaster as discussed in Barro (2006). I also show evidence suggesting that the features captured by a nonlinear model for interest rates are related to well known stylized facts of business cycles in emerging markets. In particular, the countries displaying a clear asymmetric pattern in the distribution of their real interest rates are also characterized by a high volatility of consumption relative to output and the real interest rate being strongly countercyclical and positively correlated with the trade balance. Likewise, the countries in the sample that do not show rare disaster risk in their financial conditions do not show either many of the characteristics that have been pointed out in the literature as typical of fluctuations in emerging economies.

In the second part of the chapter, I show that introducing empirically motivated nonlinearities in financial conditions in a canonical dynamic model of a small open economy can have important implications for model predictions. Interest rate shocks have been often treated as a source of fluctuations in dynamic models of small open economies (e.g. Mendoza 1991; Correia *et al.* 1995), in particular to address issues specific to emerging markets (examples include Neumeyer and Perri 2005; Uribe and Yue 2006; Mendoza 2010). However, little attention has been devoted to the specification of the stochastic process: the usual assumption is that the real interest rate the economy faces in international markets (or its log) follows a symmetric AR(1) process. In this chapter I show that the asymmetric probability distribution of interest rates found in data has quantitatively important implications for the predictions of the canonical small open economy model. The effects on the first moment of some endogenous variables suggest that the regime switching nature of the shock leads to a weaker precautionary motive for savings which, to my knowledge, is a novel result. The shift in their probability distribution is significant and can have serious implications for model calibration exercises. These results highlight the relevance of a careful specification of the shock processes in dynamic models for emerging economies, taking due account of the nonlinearities in their external conditions. The evidence in this chapter also motivates the use of global methods to solve models involving emerging economies: relying on linear approximations can involve sizeable errors.

The aim of the quantitative exercise in the second part of this chapter is to compare the equilibrium outcome of the model under mean-volatility preserving changes in the distribution of the interest rate an emerging market economy faces in international markets. The scope of the exercise is not to match data from any given country. Rather the goal is to show that fat tails in the distribution of the exogenous process can have significant implications even in the simplest neoclassical model. For this reason, the model specification is then as parsimonious as possible, and parameterized to a "typical" emerging country. In Chapter 2, instead, an extended model is carefully calibrated to Argentinean data.

The comparison of model outcomes undertaken in this chapter goes beyond second moments of the equilibrium distributions as traditionally done in the business cycle literature: The regime-switching properties of interest rates gets reflected also in lower as well as in higher moments of the distributions of endogenous variables such as output, debt, consumption and capital accumulation. The implications in terms of higher moments are important since they relate to empirical patterns of macro-aggregates from emerging countries, such as asymmetric probability distributions, and hence can help bringing standard models closer to the data. The implication in terms of the first moment has straightforward consequences for the empirical implementation of models: The presence of asymmetry in the distribution of interest rates shocks is found to shift the ergodic distribution of some endogenous variables. Consequently, the quantitative exercises in this chapter suggest that in the presence of such asymmetries model calibration should be done according to that ergodic distribution and not to non-stochastic steady state values.

The focus of this chapter on the financial conditions emerging markets face in international capital markets is justified by the relevance of changes in external financial conditions for these economies. For example, using a large panel of countries Becker and Mauro (2006) study how output drops are related to various external shocks and find that, for emerging countries, financial shocks entail the highest costs. They estimate the expected cost of each shock by computing the relative frequency of shocks, the occurrence of output collapses conditional on each shock and the size of output drops during those episodes. The authors find that, for emerging markets, the largest expected output costs relate to financial shocks that include currency crises, banking crises, debt crises and, especially, sudden

stops in capital inflows.[1] Other relevant external conditions for emerging markets such as terms of trade also display important asymmetries. A careful specification of the shocks to the terms of trade or commodity prices in dynamic models for small open economies represents a fruitful avenue for future research.

This chapter is related to the literature on "disasters" or rare events, pioneered by Rietz (1988) and more recently developed by Barro (2006) and Gabaix (2008), among others. Most of that literature explores the role of diasters, understood as the potential for infrequent large declines in aggregate output and consumption, in explaining asset pricing puzzles, and explores ways to estimate the probability and magnitude of disasters. In this line, Backus *et al.* (2009) use high-order moments such as skewness and kurtosis to measure the impact of disasters on the price of equity options. Rancière *et al.* (2008) place emphasis on asymmetries in financial variables to capture systemic risk. They use the skewness of real credit growth as a measure of systemic risk, and document the relationship between this measure and output growth for a sample of countries. In this chapter I will also inspect higher order moments of financial variables but to identify disaster events in emerging economies' access to financial markets. In particular, the focus is on specifying a stochastic process that can capture the disaster pattern of their real interest rate series and on exploring what is the effect of tail risk in dynamic models for small open economies. This chapter is also related to the work by Fernández-Villaverde *et al.* (2009) who analyze the role of changes in volatility of real interest rates in affecting real variables. They document that the volatility of real interest rates in emerging markets is not constant over time and propose a stochastic volatility model to capture this phenomenon. Then they introduce such a process into a small open economy model and show that shocks to volatility of interest rates can have distinctive effects on real variables such as consumption. The main difference with Fernández-Villaverde *et al.* (2009) is the focus in this chapter on the asymmetric pattern of financial conditions. I argue that what characterizes emerging markets' access to foreign lending is rather the potential for rare disasters: the infrequent occurrence of large and abrupt adverse realizations, partly responsible for the evidence on time-varying volatility.

The chapter is organized as follows. Section 1.2 describes the interest rate data

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[1]Besides the ones mentioned, the shocks considered in Becker and Mauro (2006) are natural disasters, terms of trade, war and political turbulence, large increases in international interest rates and oil prices.

used, presents the regime-switching empirical model and shows evidence that this provides a better characterization of interest rates in emerging markets than linear models and stochastic volatility models. It also relates the regime switching estimation results to business cycle regularities in emerging markets. Section 1.3 presents the dynamic small open economy model used for the quantitative exercises, describes the nature of the exercises and presents the results for different model specifications and parameterizations. Finally, Section 1.4 concludes.

1.2 Emerging Market Interest Rates

In this section I provide evidence of the regime switching nature of real interest rates in a sample of eight emerging economies and estimate a nonlinear model to characterize the dynamics of these time series. I show that a Markov switching autoregressive model does a better job in characterizing these interest rates than a linear representation. I also show evidence suggesting that an alternative stochastic volatility process, as the one proposed by Fernández-Villaverde *et al.* (2009), can have counterfactual predictions in terms of the probability distribution of interest rates. Finally, I relate the properties of interest rates and the estimation results from the Markov switching model with data on macro aggregates from these economies. The empirical evidence suggests that some characteristics of business cycles fluctuations in emerging markets are related to the occasional disruptions in access to foreign lending that these economies have experienced.

1.2.1 Data

The sample of emerging economies includes Argentina, Brazil, Ecuador, Mexico, Peru, Philippines, Russia and Turkey. Following the standard convention in the literature, the domestic rate for each country is constructed as the sum of a measure of the international risk free rate and a country sovereign bond spread (see Neumeyer and Perri, 2005; Uribe and Yue, 2006; Fernández-Villaverde *et al.*, 2009).[2] The choice of countries is mainly due to spreads data availability.

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[2]Although the country spread data refers to sovereign bonds, several empirical studies find evidence that sovereign interest rates and rates faced by private agents in emerging economies are closely related. For example, Mendoza and Yue (2008) report that the median correlation between sovereign interest rates and firms' financing costs for a sample of emerging economies is 0.7. Arellano and Kocherlakota (2008) also report a high correlation between country sovereign
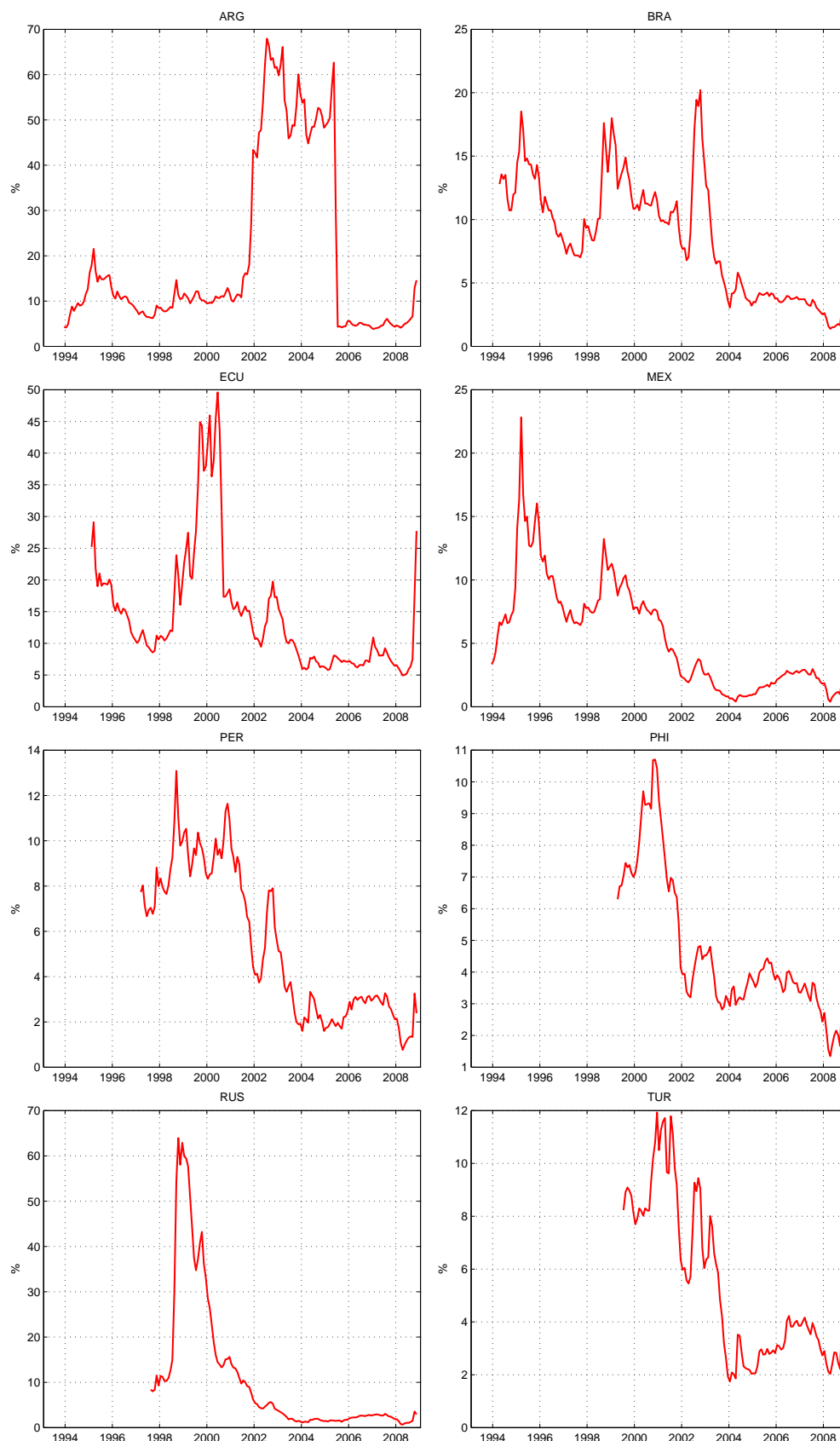
FIGURE 1.1: Real interest rates in selected emerging markets (monthly average expressed in annual basis).

The international risk free real rate is obtained by subtracting the U.S. GDP Deflator expected inflation from the annual yield on 3-month U.S. Treasury bills. Quarterly expected inflation is computed as the average of the actual GDP Deflator inflation in that quarter and in the three preceding ones. Monthly expected inflation is obtained by linearly interpolating the quarterly rate.

Country spreads series are constructed using J.P. Morgan EMBI+ Stripped Spread daily data. The EMBI+ tracks secondary market prices of emerging market bonds denominated in US dollars that satisfy given secondary market trading liquidity conditions. These indexes have been reported since December 1993, but individual countries coverage differs substantially. The sample coverage for the selected economies used in this study is reported in Table 1.1.

The real interest rate series are constructed at a monthly frequency. Since data on country spreads is available at most since December 1993, using monthly frequency allows to obtain a reasonable number of observation for many countries. Also, monthly frequency should help to identify better the shifts in mean and volatility in interest rates that might get averaged out using lower frequency data. However, the analysis on Argentinean quarterly interest rate in Section 2.2 of Chapter 2 reveals that the main qualitative features identified on the monthly sample still show up in the quarterly counterpart.[3]

1.2.2 Empirical Evidence of Regime Switching

I begin by presenting descriptive evidence on the regime switching behavior of interest rates for the sample of selected emerging economies. Figure 1.1 depicts the average monthly real interest rate (expressed in annual terms) for each country and Table 1.1 reports sample coverage and statistics. The first observation is that the sample volatility of interest rates is very high for these economies: the coefficient of variation (c.v. hereafter) ranges from 0.5 to 1.4 and the average across countries is 0.7.

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spreads and a measure of perceived probability of default of domestic private borrowers in emerging markets; the median correlation in their sample is 0.43.

[3]For the case of Argentina, it is possible to extend the series backwards, at a quarterly frequency, until 1983Q1, relying on quarterly bond return data used by Neumeyer and Perri (2005).

The second observation is that for most of the countries in the sample one or more episodes stand out in which the interest rate jumps to a much higher level and remains fluctuating at that level for some periods. Distinctive episodes in the sample include the periods following the Mexican Tequila crisis of 1994, the Russian default of 1998, the 1998 financial crisis in Ecuador, the repercussions of the 1997-1998 Asian crisis, the 1999 and 2002 crises in Brazil, the 2000-2001 crisis in Turkey and the 2001 Argentinean crisis. Several of these episodes, e.g. the Tequila crisis or the Russian default, can be simultaneously identified in the time series of different countries. Moreover, during those level shift episodes the process seems also more volatile than in tranquil times. Figure 1.2 depicts eleven-month rolling-window average and standard deviation of the real interest rate for each country.[4] The inspection of the plots reveals that periods of higher volatility coincide with periods of level shift. Indeed, the correlation between the two lines in each plot is 0.61 on average. In sum: i) there is evidence of changes in the volatility of the process over time; ii) the shifts in volatility coincide with level shifts; and iii) the overall high sample volatility of interest rates is due both to shifts in the volatility of the process but also to the fact that these coincide with shifts in its level.

The third observation is that the episodes of level and volatility shift in interest rates seem to be relatively infrequent. This impinges an important degree of asymmetry on interest rate distributions: The sample mean is bigger than the sample median for all the countries in the sample with the exception of Brazil (see Table 1.1). The ratio of the sample mean over the median ranges from almost 1 to 3.5 and the average ratio across countries is 1.6. The sample skewness, which captures the presence of a fat tail in a probability distribution, is positive in all the cases, ranging from 0.3 to 2.1.[5] Figure 1.10 show fitted densities of interest rates that confirm this asymmetric pattern for most of the economies in the sample. However, there is some heterogeneity in the sample. In particular, Brazil and Peru are in the lower end in term of the skewness of interest rates. Also their plots

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[4]For each month, the rolling-window moment includes the current observation, the 5 preceding and the 5 subsequent months.

[5]The presence of tails in interest rate distributions associated with crisis events shows up in positive skewness. An alternative moment that would signal the presence of fat tails in the sample is excess kurtosis. However, excess kurtosis would also show up due to peakedness of the distribution in comparison to a normal distribution, that is, due to the clustering of observations around the sample mean, and then excess kurtosis provides a less clear link with rare crisis events (see Rancière *et al.* 2008).
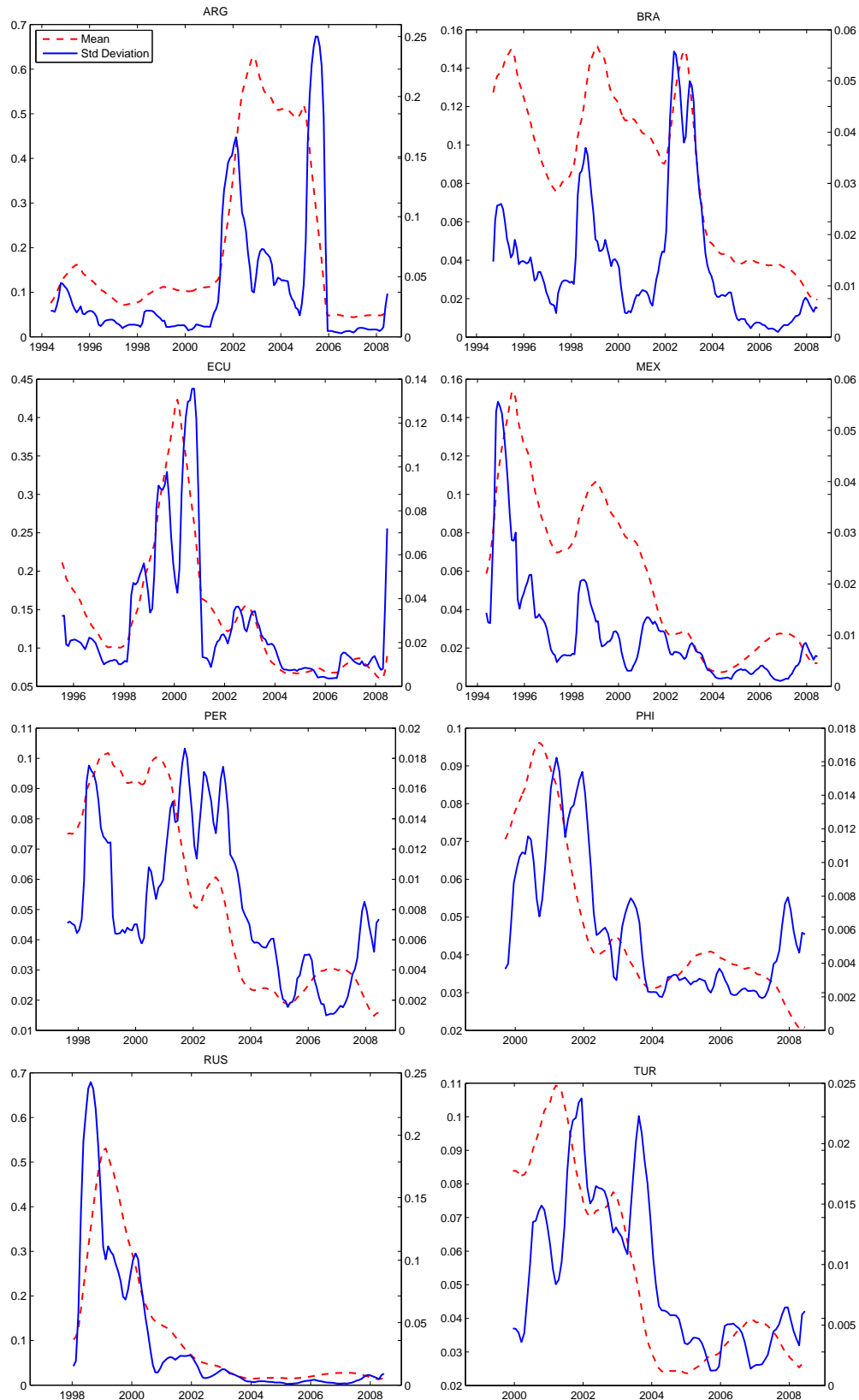
FIGURE 1.2: Real Interest Rates: Time varying level and volatility.

The dashed line represents the rolling window sample average of the real interest rate; the solid line corresponds to the rolling window standard deviation of the series. The width of the window is 11 months: For each observation the sample statistic includes the preceding and subsequent 5 months.

in Figure 1.10 show no clear pattern of asymmetry in the probability distribution if real interest rates.

1.2.3 Empirical Model

Based on the descriptive evidence presented before, simple linear models seem unlikely to be the best approximation of the interest rate dynamics faced by these economies. Instead, it motivates the use of a nonlinear process that would allow alternating between states associated with different levels and volatilities of the process, but also for the frequencies of the different states to be asymmetric. In this section I postulate the following Markov switching autoregressive model to approximate real interest rates in emerging economies:

$$r_t = \nu(s_t) + \rho_r r_{t-1} + \sigma(s_t)\epsilon_t \quad , \quad \epsilon_t \sim \text{i.i.d } N(0,1) \tag{1.1}$$

where r_t is the real interest rate and ϵ_t is white noise. The state s_t is assumed to follow an irreducible ergodic two-state Markov process with transition matrix Π. This specification allows the intercept, $\nu(s_t)$, and the standard deviations of the statistical innovation, $\sigma(s_t)$, to be regime dependent, but assumes that the persistence parameter $0 \le \rho_r < 1$ is the same across regimes.[6] More precisely, $\nu(s_t)$ and $\sigma(s_t)$ are parameter shift functions stating the dependence of the parameters on the realization of one of two regimes, which are denoted hereafter by C (crisis) and T (tranquil):

$$\{\nu(s_t), \sigma(s_t)\} = \begin{cases} \{\nu_T, \sigma_T\} & \text{if } s_t = T \\ \{\nu_C, \sigma_C\} & \text{if } s_t = C \end{cases}$$

There are therefore seven parameters to be estimated: $\nu_T, \nu_C, \rho_r, \sigma_T, \sigma_C$ and two out of the four elements in the transition matrix Π.[7]

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[6]I also considered a specification with regime switching ρ_r. However, the gain in terms of model fit was null or limited for many countries and it bears the cost of estimating an extra parameter so, for the sake of parsimoniousness, the estimated model is the same across countries and has a unique autoregressive parameter.

[7]To be more precise, there is an additional parameter to estimate: the starting period state probability, which we estimate with the smooth probability for period one; see Hamilton (1990). The estimation procedure relies on the expectation-maximization algorithm as described in Hamilton (1990). For more general references on the estimation of Markov switching models see Hamilton (1994) and Krolzig (1997).

TABLE 1.1: Real Interest Rate for a Sample of Emerging Economies, Data Statistics and Markov-Switching Model Estimates (Monthly Data).

	Argentina		Brazil		Ecuador		Mexico	
Summary Statistics:								
Sample	12/1993-11/2008		04/1994-11/2008		02/1995-11/2008		12/1993-11/2008	
Range (%)	3.8	67.9	1.4	20.2	4.9	49.6	0.4	22.8
Mean (%)	19.7		8.6		14.4		5.6	
Median (%)	10.7		8.9		11.0		4.3	
Skewness	1.2		0.3		1.8		0.9	
Std. dev. (%)	19.4		4.6		9.5		4.3	
Coeff. of Variation	1.0		0.5		0.7		0.8	
Markov Switching AR Estimation:								
Parameters:	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$
Intercept	0.26	1.25	0.08	0.46	0.57	2.69	0.04	0.68
Autoregressive	0.97		0.96		0.93		0.97	
Unconditional Mean	10.18	49.66	1.99	11.36	7.79	36.50	1.35	24.32
Standard Deviation	0.75	7.28	0.28	1.46	0.83	5.47	0.36	2.20
Transition Matrix	0.94	0.06	0.94	0.06	0.97	0.03	0.97	0.03
	0.13	0.87	0.05	0.95	0.08	0.92	0.15	0.85
Ergodic Probabilities	68%	32%	45%	55%	77%	23%	84%	16%
Linearity Test (p-value)	0.0000		0.0002		0.0000		0.0000	

	Peru		Philippines		Russia		Turkey	
Summary Statistics:								
Sample	03/1997-11/2008		04/1999-11/2008		08/1997-11/2008		07/1999-11/2008	
Range (%)	0.8	13.1	1.3	10.7	0.7	63.9	1.7	11.9
Mean (%)	5.4		4.7		10.8		5.4	
Median (%)	4.1		3.8		3.1		4.0	
Skewness	0.4		1.1		2.1		0.6	
Std. dev. (%)	3.2		2.2		15.4		3.0	
Coeff. of Variation	0.6		0.5		1.4		0.6	
Markov Switching AR Estimation:								
Parameters:	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$	$s_t = T$	$s_t = C$
Intercept	0.22	1.07	0.26	0.84	0.12	2.50	0.36	1.33
Autoregressive	0.88		0.91		0.93		0.86	
Unconditional Mean	1.89	9.06	3.00	9.65	1.62	33.72	2.53	9.41
Standard Deviation	0.29	0.80	0.31	0.64	0.33	5.87	0.32	0.91
Transition Matrix	0.96	0.04	0.99	0.01	0.96	0.04	0.95	0.05
	0.06	0.94	0.05	0.95	0.11	0.89	0.09	0.91
Ergodic Probabilities	57%	43%	81%	19%	70%	30%	64%	36%
Linearity Test (p-value)	0.0022		0.0062		0.0000		0.0036	

The unconditional mean corresponds to $\widehat{\nu}(s_t)/(1 - \widehat{\rho})$. The p-values of the likelihood ratio statistics are obtained by Monte Carlo simulations (5,000 repetitions).

Table 1.1 shows the maximum likelihood estimates of the Markov switching model for the sample of emerging economies. The estimation identifies a crisis regime characterized by both a higher average interest rate (from 3 to 20 times higher than in the tranquil regime) and higher standard deviation of the shocks (ranging from 2 to 17 times higher). This result is consistent with the estimation results in Fernández-Villaverde *et al.* 2009: when they allow innovations to the level and the volatility of country spreads to be correlated, the estimated correlation coefficient is always highly positive.

An important advantage of the Markov switching model in this context is that it allows to capture the high degree of asymmetry in the time series. In fact, the estimated parameters associated to the transition matrix reveal important asymmetries across regimes. Except for Brazil, the tranquil regime occurs more frequently than the crisis regime. For Peru the crisis regime is almost as frequent as the tranquil regime. For the remaining countries the estimated ergodic probability for the tranquil regime ranges from 64% to 84%. Conditional on being on the tranquil regime, the estimated probability of moving to the crisis regime ranges from 1% per month in the case of Philippines, to 6% per month in the case of Argentina.

An interesting by-product of the maximum likelihood estimation is the smooth probabilities of each regime, that is, the estimated probability of having been in any given regime for each point in time. The estimated smooth probabilities of the crisis regime are shown as grey areas in Figure 1.4. The model estimates assign high crisis probability to clear turbulent periods in emerging markets as, for example, the Mexican Tequila crisis, the Russian default, the 1998 financial crisis in Ecuador, the Asian crisis, the 1999 and 2002 crises in Brazil, the 2000-2001 crisis in Turkey and the 2001 Argentinean crisis. In the same vein, the estimates of crisis probabilities are consistent with several crisis indices in the literature.[8] Calvo *et al.* (2004) use data until 2001 and identify sudden stops in: Argentina in 1994, 1999 and 2001; Ecuador in 1999; Mexico in 1994; Peru in 1997; and Turkey 2001. The model for interest rate assigns a high crisis probability around all of these episodes (see Figure 1.4). The only difference with the dating in Calvo *et al.* (2004) for the periods in which the samples overlap is that the regime switching

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[8]Several of the studies that compute sudden stops or currency crisis indices report crisis dummies on an annual basis (although some of these studies use higher frequency data to identify a crisis year) and include data until 2001 or 2002 at most. The regime switching estimation refers instead to monthly data until end of 2008. Still, the comparison with the crisis indices dates can help to ratify the choice of a regime switching model for interest rates to identify systemic crises.

model also assigns a high crisis probability for the Mexican series around the time of the Russian default and the Long Term Capital Management debacle. Guidotti *et al.* (2004) also identify a sudden stop for Russia in 1998-1999 and for Philippines in 2000, all of them reflected in the crisis probabilities from the regime switching model. For the case of Brazil and based on crises indices from other studies, Rancière *et al.* (2008) report currency crises in 1995 and 1996 and banking crises from 1995 throughout 1999.[9] An advantage of the regime switching estimation vis-à-vis the crisis indices is that it also captures the severity of the rare crises in access to foreign lending.

Specification Tests. To support the choice of a nonlinear process to approximate the dynamics of interest rates in emerging markets, I test the Markov switching specification in Equation (1.1) against the null hypothesis that the interest rate is driven by an AR(1) process. More precisely, I construct the likelihood ratio test statistic $LR = \mathcal{L}_{MSAR} - \mathcal{L}_{AR}$ where $\mathcal{L}_{MSAR}$ and $\mathcal{L}_{AR}$ denote the log-likelihood of the Markov switching and the AR(1) model respectively. As pointed out by Hansen (1992), the test statistic has a nonstandard distribution in this context due to a nuisance parameters problem, so to compute critical values and p-values for the test I perform Monte Carlo simulations.[10]

The p-values for the test are reported in Table 1.1. In all cases it is possible to reject the null hypothesis at the 1% significance level, supporting the choice of a Markov switching autoregressive model as a better characterization of interest rates than a symmetric AR(1) model.

Alternative Specifications. Would a model with time varying volatility of innovations be enough to capture the main regularities of real interest rates in emerging markets? Fernández-Villaverde *et al.* (2009) provide evidence of time varying volatility in the interest rates that emerging markets face and postulate a law of motion for the interest rates in which the standard deviation of the shocks is not constant but displays stochastic volatility. More precisely, the standard

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[9]Regarding the extended quarterly sample for Argentina (1983Q1:2008Q4) that is used in Chapter 2, the mentioned studies identify crises (sudden stops, currency crises and/or banking crises) in 1983-1984, 1989-1990, 1994-1995, 1999 and 2001. All of them are picked up by the crisis probability estimates from the regime switching model.

[10]The number of repetitions in the Monte Carlo simulations to compute critical values was 5,000. Increasing the number of repetitions did not change the results.

deviation of the shock is assumed to follow an AR(1) process. This process can capture some features of real interest rate data in emerging markets, such as the time varying volatility reported in Figure 1.2. However, this specification is, by construction, symmetric: extreme negative deviations from the sample average are equally probable than positive ones, which is at odds with evidence shown in the previous section. To visualize the symmetric implication of this process, Figure 1.3 plots the fitted densities from simulating the process in Fernández-Villaverde *et al.* (2009) using their estimated parameters (posterior medians) for the Argentinean interest rate. The figure also shows the fitted density to Argentinean monthly interest rates from 1993M12 to 2008M11. The first observation is that the probability distribution of the simulated series is symmetric.[11] Second, the tails of this distribution are much more fat that in data. Indeed, the 1% and 99% quantiles of the simulated series using the stochastic volatility model are -91% and 978% respectively and in annual terms; the corresponding quantiles in data are 0.04% and 66.4%. The Markov switching model is a natural alternative to cope both with asymmetry and the level shifts that seem to characterize interest rate time series from emerging markets.[12]

1.2.4   Tails in Interest Rates and Business Cycles

This section relates the conditions that emerging economies face in international financial markets previously documented to their business cycles. The data on macroeconomic aggregates used for this purpose includes output, consumption and trade balance data. The sample coverage is: Argentina 1990Q1:2008Q2, Brazil 1991Q1:2008Q3, Ecuador 1991Q3:2008Q3, Mexico 1990Q1:2008Q2, Peru 1990Q1:2008Q2, Philippines 1990Q1:2008Q2, Russia 1995Q1:2008Q2 and Turkey 1990Q1:2008Q2. All macro aggregates have been seasonally adjusted. GDP and consumption series have been linearly detrended, unless otherwise mentioned. Monthly data is computed by linearly interpolating quarterly data.

A first observation is that the presence of tail events in interest rates is related to some of the peculiar features of business cycles in emerging markets. The literature

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[11]I also simulated 3,000 samples of 200 observations each using the process in Fernández-Villaverde *et al.* (2009) and computed the average skewness across samples. The average skewness is not statistically significantly different from zero.

[12]Figure 2.3 in Chapter 2 shows this point by displaying the distribution of the Argentinean quarterly real interest rate and the one implied by the Markov switching estimates for Argentina.
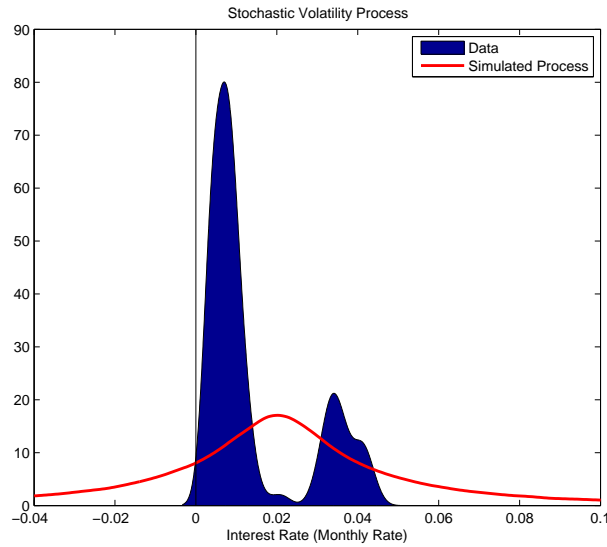
FIGURE 1.3: Stochastic Volatility Model.

The figure shows the probability distribution of the Argentinean monthly real interest rate (1993M12-2008M11) and the one implied by the stochastic volatility model according to the specification and parameter values in Fernández-Villaverde *et al.* (2009).

TABLE 1.2: Business Cycle Moments, Sample of Emerging Markets

	Relative Volatility of Consumption	Cross-correlation with Real Interest Rates	
	$std(\hat{c})/std(\hat{y})$	GDP	Trade Balance
Brazil	1.72	0.17	-0.48
Ecuador	1.07	-0.65	0.70
Mexico	1.74	-0.31	0.48
Peru	0.71	-0.01	-0.77
Philippines	0.95	-0.58	0.52
Russia	1.66	-0.74	0.63
Turkey	1.01	-0.49	0.68
Argentina	1.08	-0.86	0.80
Average:	1.24	-0.43	0.32

Monthly Consumption, GDP and trade balance data is constructing by linear interpolation of quarterly data. Trade balance refers to the trade balance to GDP ratio. The original quarterly series for Consumption and GDP are in logs and linearly detrended. The trade balance to GDP and Real Interest Rate series are not filtered nor detrended.
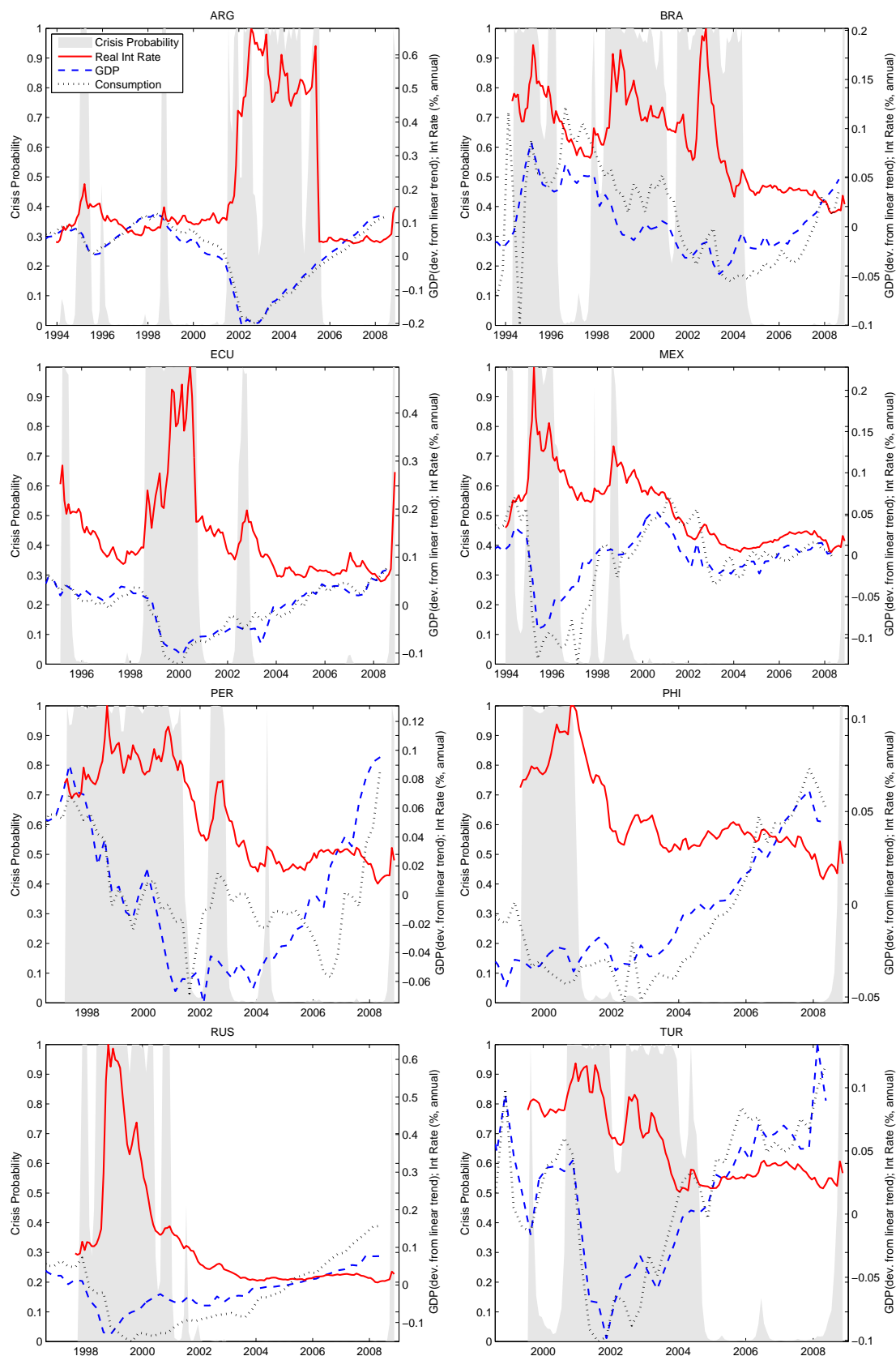
FIGURE 1.4: Real Interest Rates, linearly detrended GDP and consumption (lines) and estimated smooth probabilities for the Crisis regime (shaded area), monthly data.
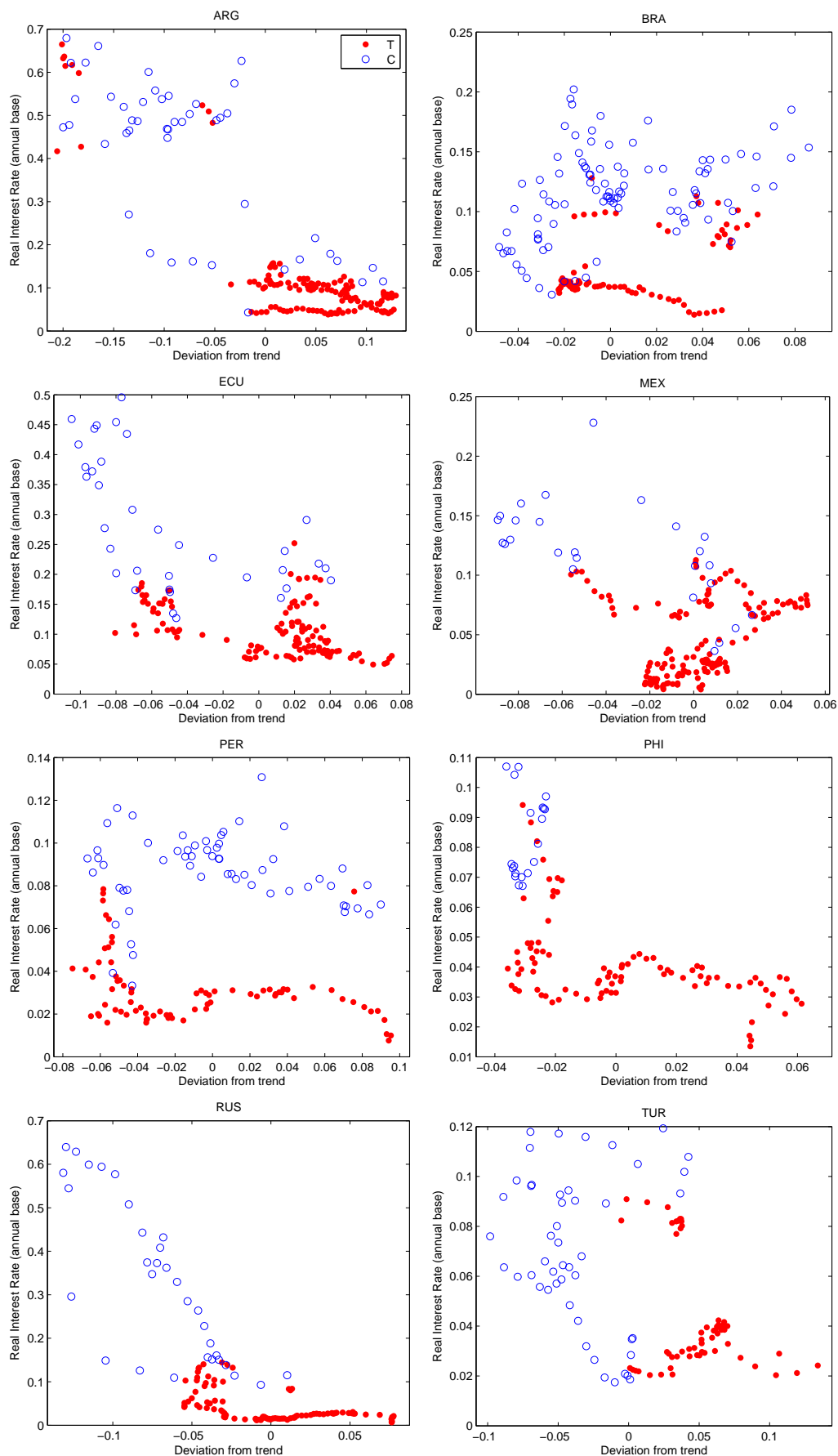
FIGURE 1.5: Real Interest Rate and linearly detrended GDP.

The solid dots indicate observations for which the estimated smooth probability for

being in the Crisis regime for interest rates is less than 50%.

TABLE 1.3: Skewness of Macroeconomic Aggregates in the Data

	GDP	Investment	Consumption	Trade Balance
Average Emerging	-0.18	-	-0.40	+0.40
Average Emerging (AG)	+0.03	-0.08	-0.24	+0.35
Average Developed (AG)	+0.01	-0.04	+0.16	-0.07

The first line corresponds to the data used for Table 1.2. The second and third lines use data from Aguiar and Gopinath (2007), which includes 13 emerging and 13 developed small open economies. GDP, consumption and investment series have been linearly detrended. The trade balance corresponds to the trade balance to GDP ratio.

on fluctuations in emerging economies has documented significant differences between traditional business cycle moments in these countries and in more advanced small open economies (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Aguiar and Gopinath, 2007). Besides higher volatility of macroeconomic aggregates and real interest rates, the most salient characteristics documented in the literature include: consumption volatility exceeds output volatility (sometimes referred to as the "volatility of consumption puzzle"), the real interest rate is strongly countercyclical, leads the cycle and is positively correlated with the trade balance. Table 1.2 reports a selection of business cycle moments for the eight economies in the sample. The averages of these moments across countries confirm indeed those stylized facts. However, there is some heterogeneity in this sample. Notably, Peru and Brazil show to be exceptions for some of these facts. Peru stands out as having a very low relative consumption volatility (it is 0.71, while the sample average is 1.24). Besides, the interest rate is practically acyclical (while the average correlation between GDP and interest rates in the sample is -0.43) and the trade balance to GDP shows a strongly negative correlation with interest rates (it is -0.77 while the average correlation is 0.32). In the case of Brazil, while the relative volatility of consumption is even higher than the sample average, it also shows a negative correlation between the interest rate and the trade balance to GDP (-0.48) and the interest rate is even procyclical (+0.17). Interestingly, these are precisely the countries for which there was a less clear asymmetric pattern in the distribution of interest rates (see Table 1.1 and Figure 1.10): they display the lowest skewness values in the sample and the estimation of the Markov switching model for these two economies attributes almost the same ergodic probability of being in the Crisis state than in the Tranquil one—while for the rest of the sample the Crisis state is a relatively rare event.

Figure 1.4 shows the time series of GDP, consumption and real interest rates as well as the estimated probability of being in the Crisis regime (shown as shaded area) for the eight emerging economies. There is a clear negative comovement between output and consumption on one side and real interest rates on the other side, and unusually large deviations from trend of macro aggregates coincide with periods of high estimated crisis probability. The average sample cross correlation between GDP and interest rates depicted in Figure 1.6 shows that interest rates are not only countercyclical but also lead the cycle in these economies, as was noted by Neumeyer and Perri (2005). The figure also depicts the cross correlation with the estimated probability of the Crisis state: a rise in the estimated crisis probability tends to be followed by a drop in activity.
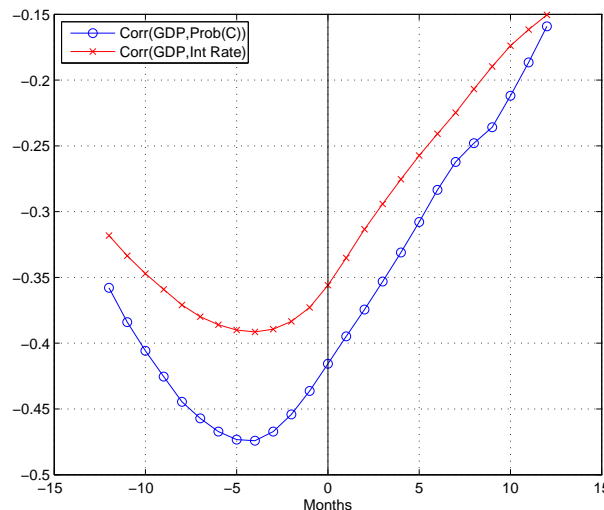
FIGURE 1.6: Cross-correlation between GDP and Real Interest Rates.
The line with crosses plots the average cross-correlation between GDP and Real Interest Rates for the sample of countries, at different leads and lags. The line with circles corresponds to the average sample cross-correlation between GDP and the estimated smooth probability of being in the Crisis regime, at different leads and lags.

Figures 1.5 and Figures 1.11 to 1.12 (these two at the end of the chapter) explore further the relationship between macro aggregates and real interest rates, distinguishing between tranquil and turbulent times according to the estimations in section 1.2.3. They show scatter plots of output (Figure 1.5), consumption (Figure 1.11) and of the trade balance to GDP ratio (Figure 1.12) against real interest rates, identifying the observations for which the estimated crisis probability

is higher than 50%.[13] Consistently with the remarks from the previous paragraphs, for most of the countries in the sample there is a clear negative (positive) relationship between deviations from trend of GDP or consumption (the trade balance to GDP ratio) on one side and real interest rates on the other. Two remarks emerge however. First, for many of the countries in the sample the strong relationship is mainly due to rare and extreme realizations. That is, during periods identified as tranquil times by the Markov switching model (shown as solid dots in the plots), the negative relationship between interest rates and GDP or consumption seems less pronounced. Also the positive relationship between trade balance and interest rates is less pronounced during tranquil times. Second and as it was the case in the evidence reported in Table 1.2, there is a clear heterogeneity in the sample: the mentioned correlations cannot be found in the plots of Brazil and Peru, the two countries which do not show a clear low probability Crisis regime in their real interest rates.

This empirical evidence suggests that what drives some of the stylized facts for emerging markets documented in the literature is mainly the occasional disruptions in access to foreign markets that the empirical model for interest rates in section 1.2.3 identifies as Crisis regimes.

A second observation is that the asymmetry found on interest rate data is also broadly found in macroeconomic aggregates. Table 1.3 reports the average skewness of macro aggregates in this sample and also in the sample of 13 emerging and 13 developed economies included in the database of Aguiar and Gopinath (2007). The comparison suggests that there are clear differences between emerging and developed economies in terms of the asymmetry of macro aggregates. Consumption displays negative skewness on average for emerging economies while it is moderately positive for developed ones. The average skewness of GDP is negative for the sample of eight emerging countries (although it is almost zero for the sample in Aguiar and Gopinath 2007) while output deviations from trend are symmetric on average for developed economies. The trade balance, instead, displays a clear positive skewness on average for emerging markets, reflecting the occasional reversals in their current accounts, while it shows no asymmetry on average for the sample of developed economies.

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[13]Figures 1.13 and 1.14 report the results using the Hodrick Prescott filter instead as detrending method. The results are very similar.

1.2.5   Concluding Remarks from the Empirical Section

Based on the regime switching estimates for a sample of eight emerging economies it is possible to conclude that the real interest rates faced by many emerging economies in international markets can be characterized as alternating between a more frequent low level/low volatility "Tranquil" regime and an infrequent high level/high volatility "Crisis" regime. Moreover, the occurrence of the infrequent Crisis regime is reflected in business cycle statistics: Some of the well known stylized facts of business cycles in emerging markets seem to be related to the presence of Crisis realizations in the sample. Similarly, those countries in the sample that do not show a clear low probability Crisis regime in their interest rates, do not show either the features documented in the literature as salient characteristics of fluctuations in emerging economies.

1.3   The Role of Regime Switching Interest Rates in Dynamic Models

In this section I use a version of the prototype dynamic small open economy model in Mendoza (1991) to analyze the implications of the regime-switching pattern of interest rates in emerging markets documented in previous sections. For clarity, along the quantitative experiments presented in this chapter the only source of uncertainty is shocks to the real interest rate.

1.3.1   The Model

The model is that of a small open economy, very similar to Mendoza (1991), Correia *et al.* (1995) or Schmitt-Grohé and Uribe (2003). Given that several papers focusing on interest rate shocks as a source of fluctuations in emerging markets have emphasized the role of financial frictions as a propagation mechanism (e.g. Neumeyer and Perri 2005; Uribe and Yue 2006), I also consider a version of the model extended to include a working capital friction. Markets are incomplete: the only financial asset is non-contingent real discount bond traded with the rest of the world.

Households and Preferences.   The economy is populated by identical, infinitely-lived households with preferences described by

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(c_t/\Gamma_t - \zeta \frac{h_t^{1+\psi}}{1+\psi}\right)^{1-\gamma} - 1}{1-\gamma} \quad , \quad 0 < \beta < 1, \gamma > 1, \psi > 0, \zeta > 0 \qquad (1.2)$$

where $c_t \geq 0$ denotes consumption and $h_t \geq 0$ is time spent in the workplace. The momentary utility function is of the form proposed by Greenwood *et al.* (1988), which is a common assumption in small open economies (Correia *et al.*, 1995). Households are the only owners of the capital stock in the economy $k_t \geq 0$, supply labor and capital to firms, receive factor payments and make consumption, saving and investment decisions. $\Gamma_t = g\Gamma_{t-1}$ measures the level of labor-augmenting technology and enters utility to ensure balanced growth; $g \geq 1$ is the economy's average productivity growth factor. The households' budget constraint in period t is

$$c_t + x_t + d_t \leq R_t^{-1} d_{t+1} + w_t h_t + r_t^k k_t \quad , \qquad (1.3)$$

where x_t are resources for investment and d_{t+1} is the households' foreign debt position in a one-period non-contingent discount bond. Households take as given the price of the bond $1/R_t < 1$, the rental rate of capital r_t^k and the real wage w_t. Long-run solvency is enforced by imposing an upper bound on foreign debt, $d_{t+1} < \Gamma_t D$, precluding households from running Ponzi-type schemes.[14] The real interest rate is assumed to be $R_t = 1 + r_t$ when $d_{t+1} \geq 0$, where the interest rate r_t is given by Equation 1.1. If instead $d_{t+1} < 0$, i.e. if domestic households become creditors in international markets, the interest rate faced by the households is $R_t = \min\{1 + r_t, \bar{R}\}$ where $\bar{R} > 1$. Without this assumption, households have strong incentives to save and accumulate unrealistic amounts of bonds when the real interest rate jumps to crisis levels. However, according to the data of Lane and Milesi-Ferretti (2007) all the emerging markets in the sample, excluding Russia because of lack of data, have been net debtors for every yearly observation between 1970 and 2004. Indeed, the net foreign asset to GDP ratio for these economies has fluctuated between -5% to -125%, with an average value across countries and periods of -44%.

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[14]In practice, the value of D is set high enough such that this constraint never binds.

The law of motion for capital, subject to quadratic capital adjustment costs, is

$$k_{t+1} \;=\; x_t + (1-\delta)\,k_t - \frac{\phi_k}{2}\left(\frac{k_{t+1}}{gk_t}-1\right)^2 k_t \; , \tag{1.4}$$

The households' problem is to choose state-contingent sequences of c_t, h_t, x_t, k_{t+1} and d_{t+1} to maximize expected utility (1.2), subject to the nonnegativity constraints, the budget constraints (1.3), the borrowing constraints and the law of motion for capital (1.4), for given prices w_t, r_t^k and R_t and initial values k_0 and d_0.

Firms and Technology. At time t a representative firm rents capital k_t and, in combination with labor input h_t produces z_t of a final good according to the production function

$$z_t = A\left(k_t^{\alpha}\left(\Gamma_t h_t\right)^{1-\alpha}\right), \qquad 0 < \alpha < 1, \tag{1.5}$$

where A is the level of productivity that, for clarity of exposition, is assumed constant throughout this exercise. The firm is entirely owned by domestic households and all factor markets are perfectly competitive. As in Uribe and Yue (2006), production is subject to a financing constraint requiring final goods producing firms to hold an amount κ_t of a non-interest bearing asset as collateral in a proportion $\varphi \geq 0$ of the cost of the wage bill at t:

$$\kappa_t \geq \varphi w_t h_t \tag{1.6}$$

The firm's problem is to choose state-contingent sequences for k_t, h_t, and κ_t in order to maximize the present discounted value of expected profits distributed to the households:

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left[z_t - w_t h_t - r_t^k k_t - \kappa_t + \kappa_{t-1}\right] \; , \tag{1.7}$$

subject to the financing constraints in (1.6) and taking as given all prices w_t, r_t^k and the representative household's marginal utility of consumption, denoted by λ_t. If the working capital parameter is set to zero ($\varphi = 0$), the problem of the firms corresponds the standard neoclassical setting.

Equilibrium   An equilibrium is a set of infinite sequences for prices r_t^k, w_t and allocations c_t, h_t, x_t, κ_t, k_{t+1}, d_{t+1} such that households and firms solve their respective problems given initial conditions k_0 and d_0 for given sequences of R_t, and labor, asset and goods markets clear. A balanced growth equilibrium is an equilibrium where c_t/Γ_t, h_t, x_t/Γ_t, k_{t+1}/Γ_t, d_{t+1}/Γ_t are stationary variables. Equilibrium conditions implied by the households' and firms' optimality conditions include (detrended variables are denoted by a hat):

$$\hat{z}_t = A\left[\left(\hat{k}_t/g\right)^\alpha h_t^{1-\alpha}\right] \tag{1.8}$$

$$\widetilde{\lambda}_t = \left(\hat{c}_t - \zeta\frac{h_t^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{1.9}$$

$$\zeta h_t^\psi = \left(1 + \varphi\left(\frac{R_t - 1}{R_t}\right)\right)^{-1}(1-\alpha)\frac{\hat{z}_t}{h_t} \tag{1.10}$$

$$\widetilde{\lambda}_t = \frac{\beta}{g}\mathrm{E}_t\left[\widetilde{\lambda}_{t+1}\right]R_t \tag{1.11}$$

$$\widetilde{\lambda}_t\left(1 + \frac{\phi_k}{g}\left(\frac{\hat{k}_{t+1}}{\hat{k}_t} - 1\right)\right) = \frac{\beta}{g}\mathrm{E}_t\left[\widetilde{\lambda}_{t+1}\left(\alpha\frac{g\hat{z}_{t+1}}{\hat{k}_{t+1}} + 1 - \delta + \frac{\phi_k}{2}\left(\left(\frac{\hat{k}_{t+2}}{\hat{k}_{t+1}}\right)^2 - 1\right)\right)\right] \tag{1.12}$$

The financial friction parameter φ appears in equation (1.10), introducing a wedge between the marginal rate of substitution between leisure and consumption and the marginal product of labor. Setting $\varphi = 0$ recovers the frictionless neoclassical small open economy model. For the quantitative analysis I will assume both zero and positive values for this parameter.

Finally, the resource constraint is

$$\hat{c}_t + \hat{x}_t + \hat{nx}_t = \hat{y}_t \tag{1.13}$$

where $\hat{nx}_t$ are (detrended) net exports, given by $\hat{nx}_t = \frac{\hat{d}_t}{g} - R_t^{-1}\hat{d}_{t+1}$, and $\hat{y}_t$ is detrended GDP.[15] The household's debt position $\hat{d}_t$ is the economy's net foreign debt position in period t, and the trade balance, or net exports, are all resources not used for consumption and investment.

1.3.2   Quantitative Analysis

The purpose of the quantitative exercises in this section is to explore the implications of the regime switching behavior of interest rates. For a given parametrization

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[15]GDP is given by $y_t = w_t h_t + r_t^k k_t = \left(\alpha + \frac{1-\alpha}{1+\varphi\left(\frac{R_t-1}{R_t}\right)}\right)z_t$.

of the model, the main quantitative experiment consists in introducing a mean-variance preserving modification in the stochastic process for interest rates in a way such that it removes all the asymmetry in its probability distribution. The model is not calibrated to match data from one economy in particular. Instead, the objective of the quantitative exercises is to understand the implications of the fat tails found in interest rate data from emerging economies.

The parameter values used for the quantitative analysis are reported in Table 1.5. Most of the values correspond to the ones used for the model calibrated to Argentinean data in chapter 2, section 2.5.3.[16] The benchmark parametrization corresponds to the simplest possible model: a neoclassical small open economy model with no frictions and abstracting from secular growth. Subsequently, the exercise is repeated for different parameterizations: First, I introduce a financial friction in the form of a working capital constraint (by setting $\varphi > 0$). Then, I allow for deterministic growth in the model (i.e. $g > 1$). Finally, I consider different values for the average interest rate.[17] In all of these different calibrations, the only parameter that is also modified is the capital depreciation rate δ, in order to keep the investment-output ratio constant across calibrations.

1.3.2.1   Real Interest Rate Process

The data generating processes (DGP) for the real interest rate in each experiment are both a Markov switching autoregressive model as in equation (1.1), and a mean-variance preserving linear AR(1) approximation. The parameters used for the nonlinear DGP are shown in Table 1.6. The parameter values are not intended to be fully realistic or to match the interest rate of one given country in the sample, but they do imply interest rate fluctuations that are qualitatively consistent with the empirical findings of the previous section: interest rates switch between a more frequent low level/low volatility regime and an infrequent high level/high volatility regime. In this sense, the parameters are such that the mean and the volatility under the crisis regime is approximately 2 times larger than under the tranquil regime. The transition matrix is such that, conditional on being on the

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[16]The model used in that section is the same used in this chapter when including financial frictions, except that total factor productivity is stochastic and it includes a portfolio adjustment cost function.

[17]Assuming different values for the average interest rate is equivalent to modify the discount factor β while keeping constant the average interest rate.

Tranquil regime there is a 5% probability of switching to the Crisis regime, while the probability of remaining in the Crisis regime is 55%.[18] These parameters for the transition matrix imply that the Crisis regime is a rare state: it occurs 10% of the time. The degree of asymmetry implied by those ratios is in the lower end of the estimation results reported in the previous section (see Table 1.1): the ratio of estimates for the unconditional mean across regimes ranges from 1.4 to 20 while the ratio for the standard deviation of the innovations ranges from 2 to 17.
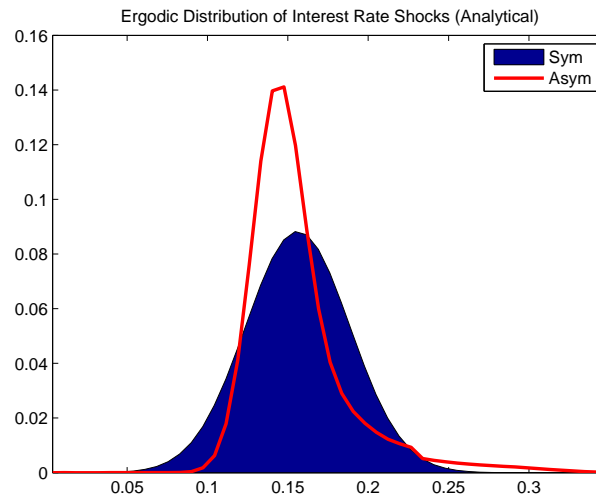
FIGURE 1.7: Distribution of the asymmetric and symmetric DGP for the interest rate

To obtain a mean-variance preserving approximation to the nonlinear DGP I proceed as follows. First, I compute a discrete approximation to the Markov switching process on a grid of equidistant nodes. Using the transition matrix of this approximation I obtain analytically the moments of its ergodic distribution. Then, I compute a new approximation that has the same fist two moments (mean and standard deviation), but is symmetric (i.e. zero skewness). The fitted densities of the interest rate from the regime switching process and the linear process are shown in Figure 1.7: the nonlinear DGP clearly displays a fat tail to the right, reflecting the low probability of very high interest rates. Section I of Table 1.4 reports the analytical moments from their ergodic distributions: the averages and standard

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[18]Both the probabilities of remaining in the Tranquil and in the Crisis regime are lower than the ones reported in Table 1.1 for the estimations using monthly data. The reason is that the model in this section is parameterized at a quarterly rather than monthly frequency, borrowing the parameters used for some of the exercises of chapter 2. Still, the expected duration in each regime is consistent with the monthly estimates. The expected duration in the crisis regime is between 2 and 3 quarters. The estimates in Table 1.1 imply, for example, 7 months for Mexico, 8 for Argentina and 12 for Ecuador, the average duration being 10 months (excluding Brazil and Peru).

deviation of the two precesses are equal, while the skewness of the nonlinear DGP is positive and high.

Solution Method. For each parametrization of the model and each discrete approximation to the interest rate process (i.e. symmetric and asymmetric), the policy functions for the state variables $\hat{d}_{t+1}$ and $\hat{k}_{t+1}$ are approximated by piecewise linear functions over a grid. A global approximation of the equilibrium dynamics is obtained by iterating over the intertemporal Euler conditions, as suggested by Coleman (1990). The standard iteration procedure is generally slow and is therefore combined with the method of endogenous gridpoints, proposed by Carroll (2006).[19]

1.3.3 Simulation Results

The first set of simulation results correspond to the frictionless version of a model with no deterministic growth (i.e. $\varphi = 0$ and $g = 1$). Table 1.4 displays summary statistics of the probability distributions of some key variables for interest rate realizations drawn from both stochastic processes. Even though both processes have identical first and second order moments, results in Table 1.4 show that the probability distribution of the endogenous variables can be substantially different.

A first observation is the large difference in the average external debt to GDP ratio: it is substantially higher under the nonlinear specification than under the linear specification (see section II.a in Table 1.4). Indeed, while the average of the ergodic distribution of the debt to GDP ratio when the economy faces a symmetric shock is 0.74, when the nonlinear shock is feeded the average ratio is 1.12, that is 52% higher. The shift to the right of the debt to GDP distribution under the asymmetric shock can be clearly seen in the top plot in Figure 1.8.

The different levels of average debt to GDP ratio illustrate how the nature of the uncertainty faced by optimizing agents can affect precautionary savings behavior. Agents self insure in different ways against interest rates that are volatile all the time, or interest rates that switch between tranquil and rare crisis regimes. The intuition for this result can be understood by comparing the one-period ahead

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[19]The algorithm is presented in detail in Appendix 1.5.1.

TABLE 1.4: Simulation results for benchmark model

	Asymmetric Shock	Symmetric Shock	% dif.
I) REAL INTEREST RATE			
I.a) Analytical Moments			
Unconditional Mean (%)	15.61%	15.61%	
Standard Deviation (%)	3.24%	3.24%	
Skewness	1.91	0.00	
Autocorrelation	0.85	0.85	
II) ENDOGENOUS VARIABLES			
II.a) Unconditional Means			
Debt to GDP	1.12	0.74	+52.0%
Capital to GDP	4.23	4.23	+0.01%
Consumption to GDP	0.74	0.75	-1.84%
Net Exports to GDP (%)	3.97%	2.58%	+53.9%
II.b) Standard Deviations			
Output (%)	0.49%	0.72%	
Consumption $std(\hat{c})/std(\hat{y})$	1.98	1.54	
Investment $std(\hat{x})/std(\hat{y})$	5.68	4.56	
Trade balance to GDP (%)	1.10%	1.44%	
II.c) Skewness			
Output	-0.16	0.01	
Consumption	-1.35	0.08	
Investment	-1.53	0.10	
Trade balance to GDP	1.80	-0.13	
II.d) Cross-Correlations with Output			
Consumption	0.38	0.36	
Investment	0.22	0.29	
Trade balance to GDP	0.07	0.14	
II.e) Cross-Correlations with Real Interest Rate			
Output	-0.13	-0.12	
Consumption	-0.89	-0.91	
Investment	-0.93	-0.93	
Trade balance to GDP	0.93	0.93	

GDP, consumption and investment series have been linearly detrended. The trade balance corresponds to the trade balance to GDP ratio.
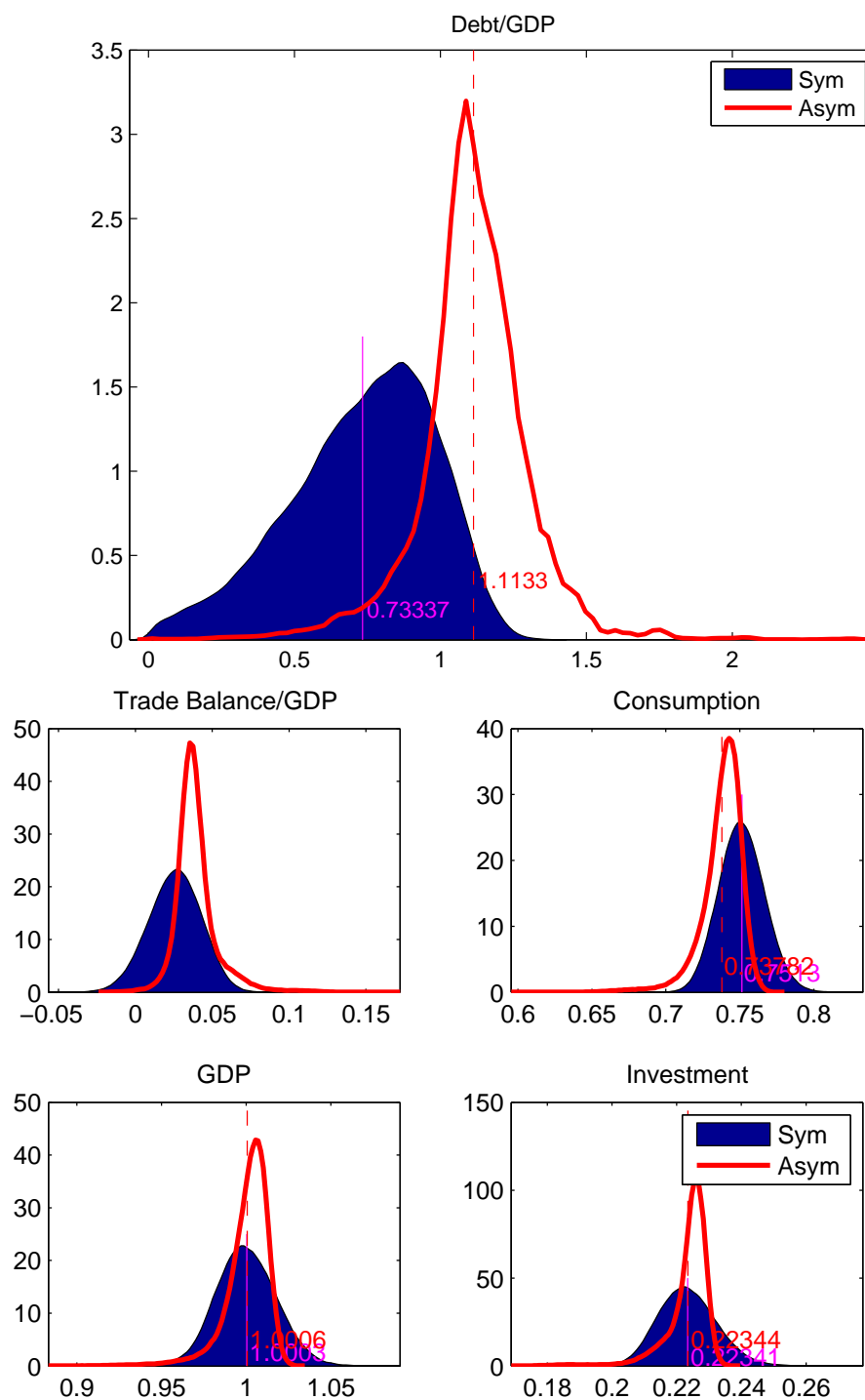
FIGURE 1.8: Distribution of model simulated series under the different processes for the interest rates. In both cases the model is solved using a global nonlinear solution method.

conditional expectation and forecast variance for the interest rate under the linear and nonlinear specification, conditional on the current interest rate being equal to the unconditional mean, 15.61%. Figure 1.9 depicts the probability distributions of forecasts under the linear and nonlinear DGP, conditional on each regime for the latter. Under the nonlinear DGP and conditional on being on the Tranquil regime, the one period ahead forecast is 15.40%, lower than the unconditional mean, and its standard deviation is only 1.47%. Instead, under the symmetric DGP, the point estimate for next period interest rate is higher (it coincides with the actual level) and the standard deviation of the forecast is also higher: 1.69%. Both a higher point estimate and a higher uncertainty about next period's interest rate would be associated with a lower demand for foreign debt than under the nonlinear DGP at the Tranquil regime. Of course, conditional on being on the Crisis regime instead the point forecast would be higher than the long run level (17.4%) and much less precise (the standard deviation of forecast would be 2.7%). However the asymmetric frequency across regimes implies that the economy is only 10% of the time in the Crisis regime, which determines that even if the long run level and volatility of interest rates and all structural parameters (including the discount factor) are the same under both specifications, the demand for foreign debt is higher when the cost of borrowing shows tail risk.
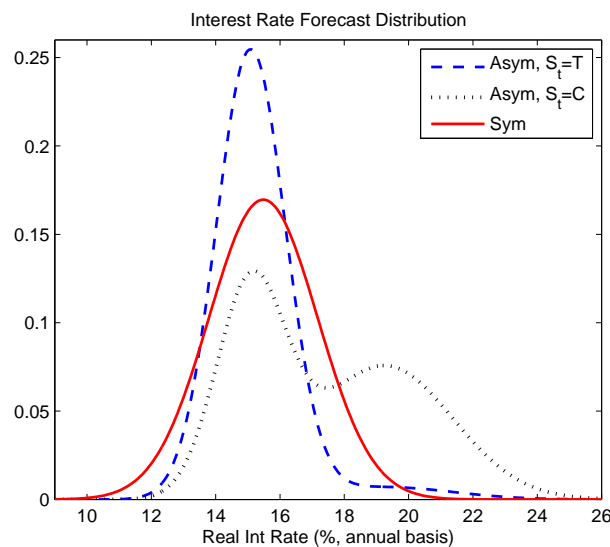
FIGURE 1.9: Distribution of Interest Rate Forecasts
Distribution of forecasts for R_{t+1} conditional on R_t being equal to the long-run mean, 15.61%. The solid line corresponds to the symmetric DGP, the dashed and dotted line correspond to the nonlinear DGP, conditional on $s_t = T$ and $s_t = C$ respectively.

The differences in first moments of distributions have important implications. In terms of calibrating models, it is well understood that the presence of uncertainty might imply the ergodic distribution of endogenous variables to shift away from the deterministic steady state of a model. This exercise shows that also the pattern of the uncertainty processes, in particular its asymmetry, can have large implications in terms of first moments of some endogenous variables. In other words, ignoring the nonlinearity of the interest rate found in data for emerging economies might lead to important mistakes in calibration exercises.

A second result that stands out is that the presence of tails in the interest rate distribution also affects some of the second moments of the endogenous variables. For example, the relative standard deviation of consumption, a statistic that typically receives much attention in emerging market business cycle studies, is significantly greater under the nonlinear specification.

Finally, both specifications have different implications for the skewness of the variables, as it is clear from section II.c) in Table 1.4. Whereas the model with symmetrically distributed shocks implies fairly symmetric distributions for the equilibrium values, the simulations with asymmetrically distributed interest rates produces important asymmetries in the distributions of the endogenous variables. The fitted densities of simulated output, consumption, investment and trade balance-to-GDP series shown in Figure 1.8 reflect these differences. For example, the sample skewness of consumption in the model with asymmetrically distributed shocks is -1.35 while it is 0.08 when the distribution of the shock is symmetric. In the case if investment the sample skewness is -1.53 when the shock is asymmetric and 0.10 otherwise. The sample skewness of GDP in this frictionless version of the model is mainly related to the skewness of investment: it is also negative in the model with an asymmetric pattern for the uncertainty process while almost zero for the symmetric case. The presence of a tail to the right in interest rates gets also reflected in occasional reversals in the trade balance: the skewness of the trade balance to GDP ratio is positive and high (1.80) under the asymmetric interest rate shocks, while slightly negative (-0.13) when the distribution of interest rates is symmetric.

The properties of higher order moments are particularly relevant when analyzing fluctuations in emerging markets. The empirical evidence in Section 1.2.4 suggests that business cycle fluctuations in emerging economies and more developed

small open economies also differ in terms of the sample skewness of their main macroeconomic aggregates. In this sense, models predicting symmetric distributions of its endogenous variables would be missing a very defining characteristic of fluctuations in emerging economies.

Model with Financial Frictions. Columns 3 and 4 in Table 1.7 show the results for the same exercise but for the model with financial frictions. More precisely, the only difference with the benchmark parametrization is that $\varphi = 1$. In this model and as pointed out by Neumeyer and Perri (2005) and Uribe and Yue (2006), interest rate shocks affect the marginal productivity of labor inputs, and consequently output contemporaneously. The effect of the financial friction in labor productivity gets reflected in the volatility of simulated output: the standard deviation of GDP is 0.67% in the model with frictions while it is 0.49% in the benchmark model, when considering asymmetric shocks in both cases (moments for the benchmark parametrization are repeated for convenience in columns 1 and 2 of Table 1.7).

The main difference in the model with frictions regarding the effects of asymmetries in interest rates is reflected in higher order moments of the distribution of output. The probability distribution of output is more asymmetric in the presence of financial frictions, reflecting occasional severe drops in GDP. The skewness of GDP is -0.32 while it is -0.16 in the frictionless model. Another relevant effect of the asymmetry of the shock in the model with financial frictions is that the countercyclicality of the trade balance, a key moment for emerging economies, is significantly greater with asymmetric shocks: it is -0.28 under the symmetric shock while it is -0.49 under the nonlinear specification (not reported in Table 1.7 to save space).

Higher Average Real Interest Rate. The results for a third set of simulations considering a higher average real interest rate are reported in columns 5 and 6 of Table 1.7. The purpose of this alternative process is to analyze the effect of narrowing the gap between the (average) interest rate and the inverse of the discount factor. The annual rate implied by β is 15.66% while in the benchmark parametrization the average interest rate is 15.61%. Alternative, for the exercise in this section the average real interest rate interest rate is 15.64%. The degree of

asymmetry of the interest rate processes are unchanged though.

The main effect of a higher average interest rate (a lower gap with the rate implied by the discount factor) is reflected in the first moment of the endogenous variables. With a lower gap, the average debt to GDP ratio is lower than in the benchmark case for both the symmetric and asymmetric shocks. However, also the distance between the two ratios is smaller: it is 43% bigger under the nonlinear specification than under the linear specification, while under the benchmark parametrization it was 52% higher instead. The lower average trade balance to GDP ratios under this parametrization reflect lower amounts of interest payments due to lower levels of debt on average.

Deterministic Growth In all the sets of simulations reported before I have abstracted from growth ($g = 1$). However, calibration exercises typically take into account secular growth in the economy. The set of simulations in this section explore whether allowing for deterministic growth has any influence in the way the asymmetry of interest rate shocks affects the model's endogenous variables. The value used for g corresponds to the average growth rate of output in Argentina used for the calibration exercise in Chapter 2.[20] The results are reported in columns 7 and 8 of Table 1.7.

Positive productivity growth is reflected in a higher capital to GDP ratio on average, irrespective of the pattern of the interest rate shock. Nonetheless, the main result from the numerical exercise in this section is that none of the effects of the asymmetry of interest rates distributions depends on the presence of deterministic growth.

1.4 Conclusion

The empirical evidence in this chapter shows that the most salient feature of financial conditions for emerging markets is not that they are volatile but rather that they show a rare disaster pattern. These countries occasionally experience large and abrupt deteriorations in conditions of access to foreign borrowing. This

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[20]When adjusting g also β is adjusted to keep the degree of impatience as in the benchmark parametrization (see Table 1.5).

pattern is reflected in the real interest rate they face in international markets, that can be characterized as alternating between periods of low level and volatility and rare periods in which the interest rate jumps to a higher level and displays higher volatility than outside those episodes. This chapter shows that a Markov switching autoregressive model can capture many of these features and that it provides a better characterization of the process than either a linear model or a stochastic volatility one.

The chapter also provides evidence that the occurrence of the crisis regime identified by the empirical model for interest rates is associated with some of the well known stylized facts of business cycles in emerging markets for many of the countries in the sample. In the same vein, the countries in the sample that do not show rare disaster risk in their financial conditions do not show either the characteristics that have been pointed out in the literature as typical of fluctuations in emerging economies.

The asymmetries in interest rates found for many of the countries in the sample have important implications for the canonical small open economy model used in the literature. The presence of asymmetries in the exogenous state affects significantly the ergodic distributions of the endogenous variables affecting both their first, second and higher order moments. The effects in terms of second (volatility) and third (asymmetry) moments are significant and can potentially help to bring small open economy models closer to data from emerging economies along several dimensions. The effects in terms of the first moment suggest that the regime switching nature of the shock leads to a weaker precautionary motive for savings which, to my knowledge, is a novel result. The shift in the distribution of endogenous variables is significant and can have serious implications for model calibration exercises. Overall, the results in this chapter highlight the importance of specifying the exogenous processes in dynamic models for emerging economies in a consistent manner, taking due account of the nonlinearities they face in external conditions. Models fed with linear and symmetric processes and solved using linear approximation methods might miss several features relevant for these economies.

While this is not the first study to use a small open economy assumption for interest rates in emerging economies, a caveat is of order. Some of the external

conditions in emerging economies that show a rare disaster pattern are fully exogenous (e.g. the terms of trade for some commodity exporters). However, the country spread component of interest rates arguably includes an endogenous default risk element. In this sense, the exogenous regime switching modeling approach in this chapter would represent a shortcoming. The reason for this assumption is, first, that it allows to feed the model with a process for interest rates that is consistent with the pattern found in data, reflecting the occasional disruptions in emerging economies' access to foreign lending, while keeping the structure of the model simple and tractable. Moreover, what country spreads capture is the foreign investors' perceived probability of default rather than the objective probability, and hence might not be necessarily driven by changes in domestic fundamentals. In that sense, the regime switching nature of interest rates we find in data might respond to abrupt shifts in investors' expectations about, for instance, the willingness of other investors to rollover short term debt, or about the future path of domestic policy, elements which might also respond to developments in other economies. To the extent that these phenomena play an important role in the pricing of emerging markets' debt as many empirical studies suggest, treating these shifts in investors perceptions as triggered by exogenous regime switches seems a reasonable first approximation.

1.5 Appendix Chapter 1

1.5.1 Numerical Algorithm

The algorithm seeks an approximate solution to the system of stochastic difference equations comprising Equation 1.8 to Equation 1.13. Denoting the vector of state variables by $S_t = \left[\hat{k}_t, \hat{d}_t, R_t, s_t\right]$, the policy functions for the state variables $\hat{d}_{t+1} = d(S_t)$ and $\hat{k}_{t+1} = k(S_t)$ is approximated by piecewise linear functions over a grid, denoted by S, of $21 \times 61 \times 51 \times 2 = 130,662$ nodes each and the approximate solution is computed by iterating over the policy functions (Coleman 1990). The procedure is combined with the method of endogenous gridpoints in Carroll (2006) to speed up the algorithm. More specifically, the algorithm is:

Step 1 Postulate an initial guess $k_0(S)$ and $d_0(S)$.

Step 2 Given the last guess $k_{j-1}(S)$ and $d_{j-1}(S)$, calculate $k'' = k_{j-1}(S)$, $d'' = d_{j-1}(S)$ and find c', z', h', λ' using Equations 1.8-1.13.

Step 3 Compute

$$
e_1 = \frac{\beta}{g}\mathrm{E}\left[\lambda'|R,s\right]
$$

$$
e_2 = \frac{\beta}{g}\mathrm{E}\left[\lambda'\left(\alpha\frac{gz'}{k'} + 1 - \delta + \frac{\phi_k}{2}\left(\left(\frac{k''}{k'}\right)^2 - 1\right)\right)|R,s\right]
$$

and solve for d and k, using

$$
e_1 = \lambda R^{-1}
$$

$$
e_2 = \lambda\left(1 + \frac{\phi_k}{g}\left(\frac{k'}{k} - 1\right)\right)
$$

as well as Equations 1.8-1.13.

Step 4 Using k', d' and k, d, R and s, interpolate to obtain $k'' = k_j(S)$ and $d'' = d_j(S)$.

Step 5 Repeat step 2 to 4 until convergence.

TABLE 1.5: Model Parametrization

a) Preferences	Symbol	Benchmark	Alternative
Discount factor	β/g	0.9643	
Utility curvature	γ	2	
Labor disutility weight	ζ	0.62	
Inverse wage elasticity of labor supply	ψ	0.6	
b) Technology			
Capital income share	α	0.38	
Growth factor	g	1.0083	1
Working capital requirement	φ	1	0
Capital depreciation parameter	δ	0.033	varies[1]
Capital adjustment cost	$\phi_k/2$	10	
Saving interest rate ceiling	$\bar{R}$	$1.02^{1/4}$	

Notes: [1]In each parametrization δ is adjusted such that the investment-output ratio is kept constant.

1.5.2 Other Tables and Figures

TABLE 1.6: Parameters of Real Interest Rate Process.

Nonlinear DGP

Unconditional Mean		Autoregressive	Standard Deviation	
Tranquil	Crisis		Tranquil	Crisis
14.1%	28.2%	0.70	1.06%	2.12%

Transition Matrix			Ergodic Probabilities	
			Tranquil	Crisis
0.95	0.05		90%	10%
0.45	0.55			

AR(1) approximation

Unconditional Mean	Autoregressive	Standard Deviation
15.61%	0.85	1.68%

TABLE 1.7: Simulation results for alternative parameter values

	Benchmark		Financial Frictions		Higher Int Rate		Det. Growth	
	Asym. Shock	Sym. Shock	Asym. Shock	Sym. Shock	Asym. Shock	Sym. Shock	Asym. Shock	Sym. Shock
I) REAL INTEREST RATE								
I.a) Analytical Moments								
Unconditional Mean (%)	15.61%	15.61%	15.61%	15.61%	15.64%	15.64%	15.61%	15.61%
Standard Deviation (%)	3.24%	3.24%	3.24%	3.24%	3.24%	3.25%	3.25%	3.24%
Skewness	1.91	0.00	1.91	0.00	1.91	0.00	1.91	0.00
Autocorrelation	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
II) ENDOGENOUS VARIABLES								
II.a) Unconditional Means								
Debt to GDP	1.12	0.74	1.11	0.73	0.83	0.58	1.15	0.74
Capital to GDP	4.23	4.23	4.23	4.23	4.23	4.23	5.50	5.50
Consumption to GDP	0.74	0.75	0.74	0.75	0.75	0.76	0.75	0.76
Net Exports to GDP (%)	3.97%	2.58%	3.93%	2.56%	2.93%	2.02%	3.10%	1.96%
II.b) Standard Deviations								
Output (%)	0.49%	0.72%	0.67%	0.89%	0.48%	0.71%	0.51%	0.76%
Consumption $std(\hat{c})/std(\hat{y})$	1.98	1.54	2.13	1.83	1.88	1.50	1.90	1.49
Investment $std(\hat{x})/std(\hat{y})$	5.68	4.56	3.96	3.79	5.68	4.57	7.32	5.77
Trade balance to GDP (%)	1.10%	1.44%	1.15%	1.49%	1.08%	1.42%	1.28%	1.69%
II.c) Skewness								
Output	-0.16	0.01	-0.32	0.02	-0.16	0.01	-0.15	0.01
Consumption	-1.35	0.08	-1.29	0.07	-1.42	0.09	-1.36	0.08
Investment	-1.53	0.10	-1.54	0.11	-1.52	0.12	-1.65	0.10
Trade balance to GDP	1.80	-0.13	1.82	-0.11	1.74	-0.11	1.80	-0.14
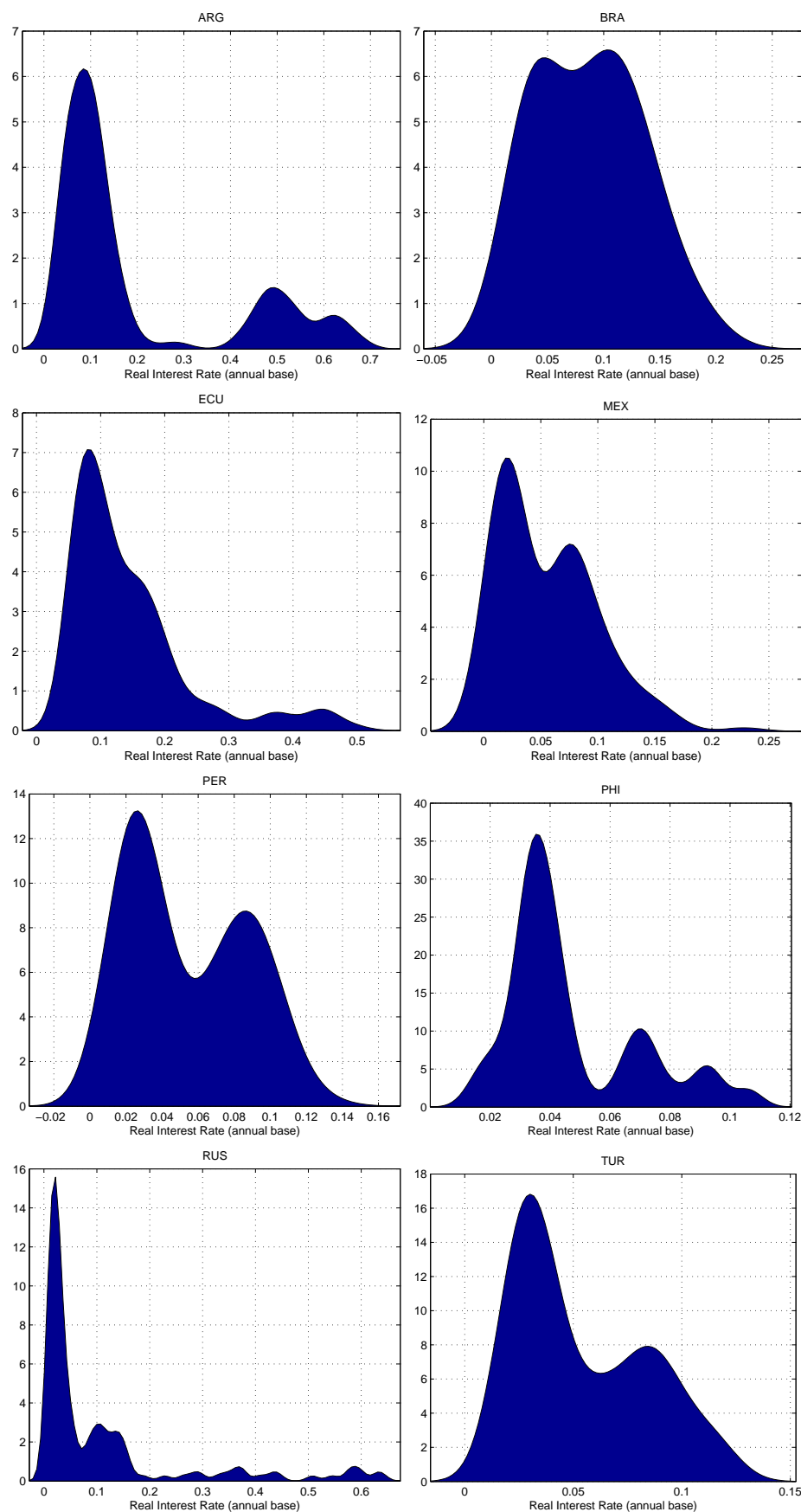
FIGURE 1.10: Fitted Densities of Real Interest Rates in Emerging Economies (monthly data).
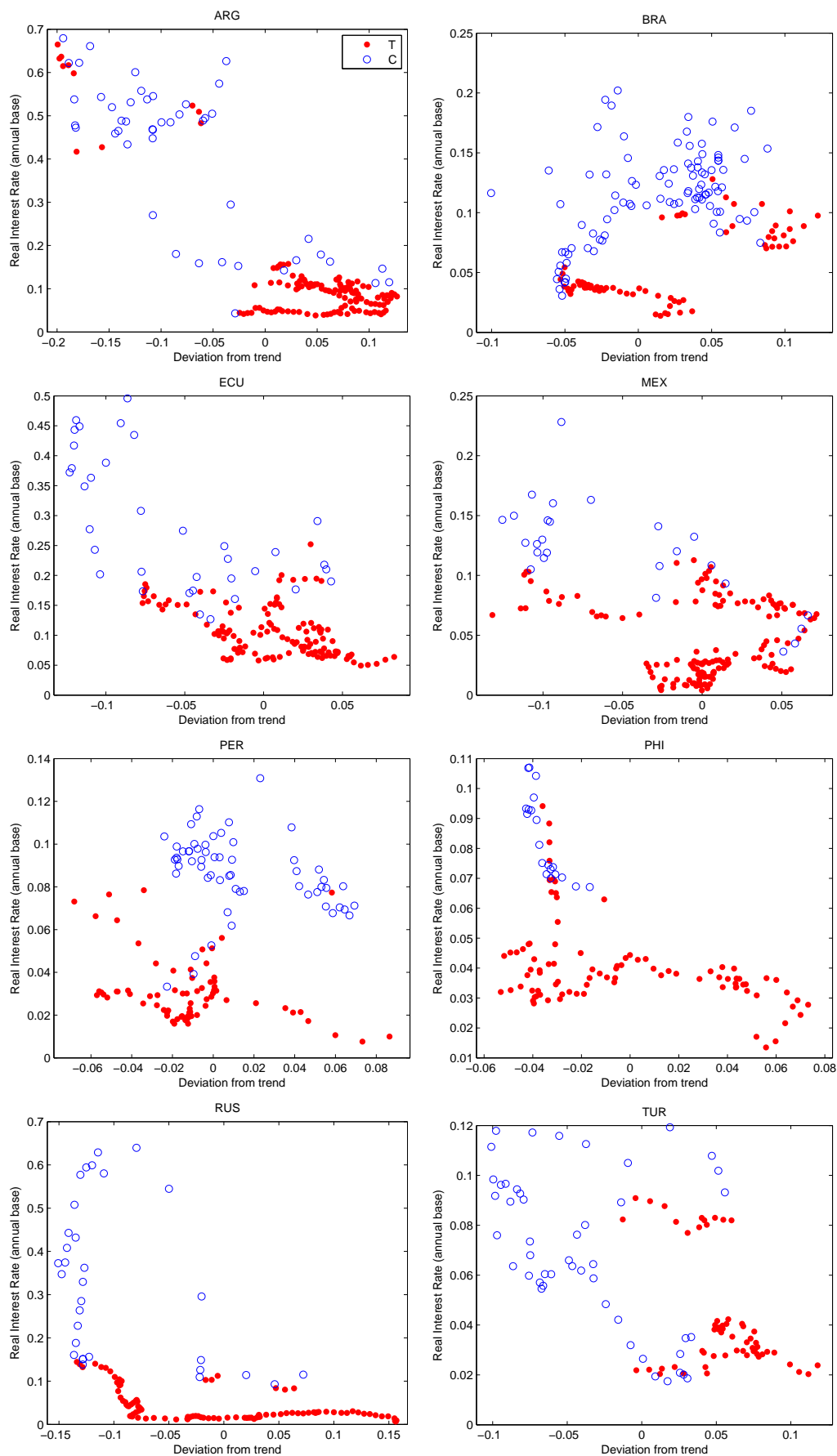
FIGURE 1.11: Real Interest Rates and linearly detrended Consumption.

The solid dots indicate observations for which the estimated smooth probability for being in the Crisis regime for interest rates is less than 50%.
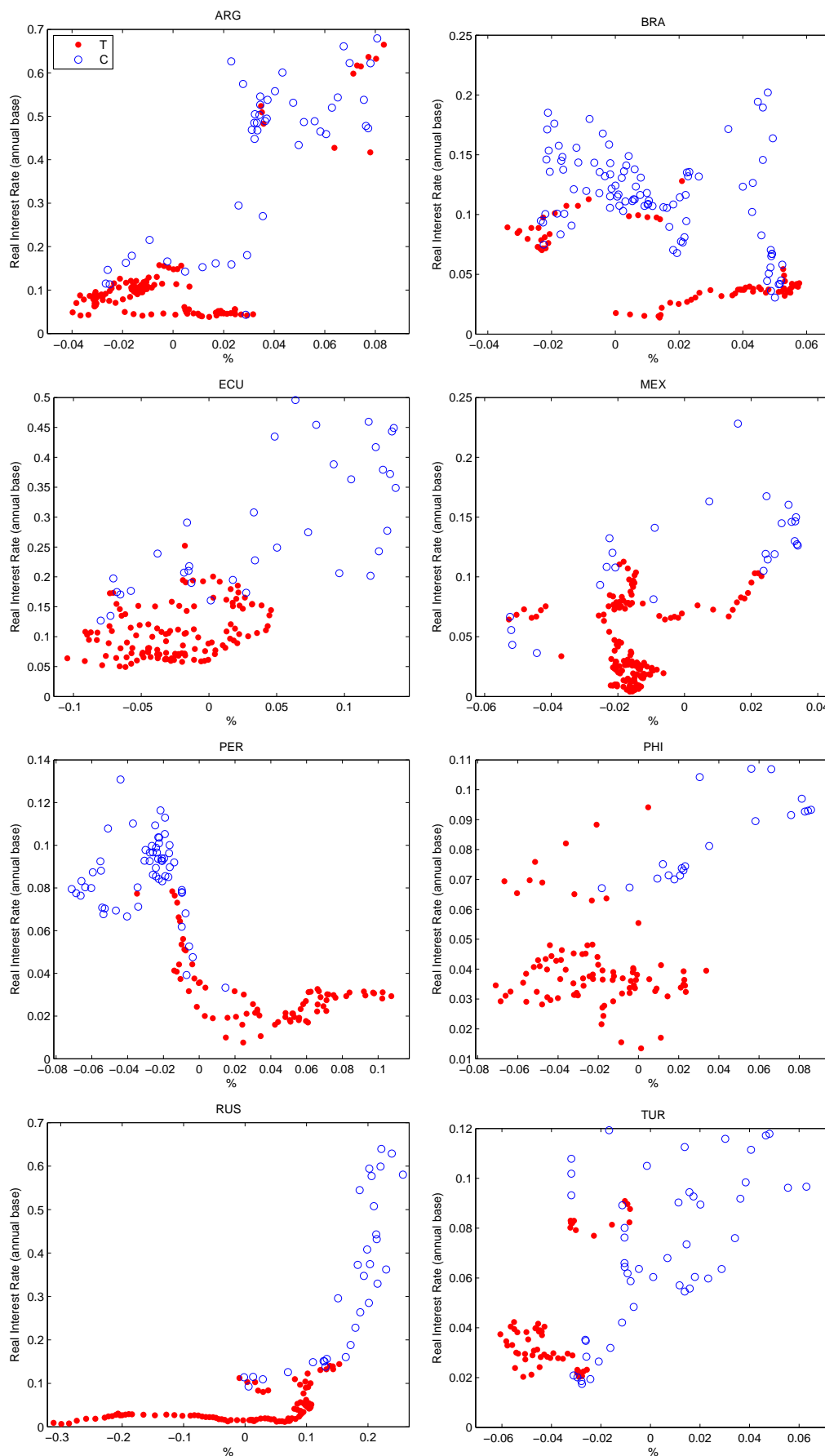
FIGURE 1.12: Real Interest Rates and Trade Balance.

The solid dots indicate observations for which the estimated smooth probability for

being in the Crisis regime for interest rates is less than 50%.
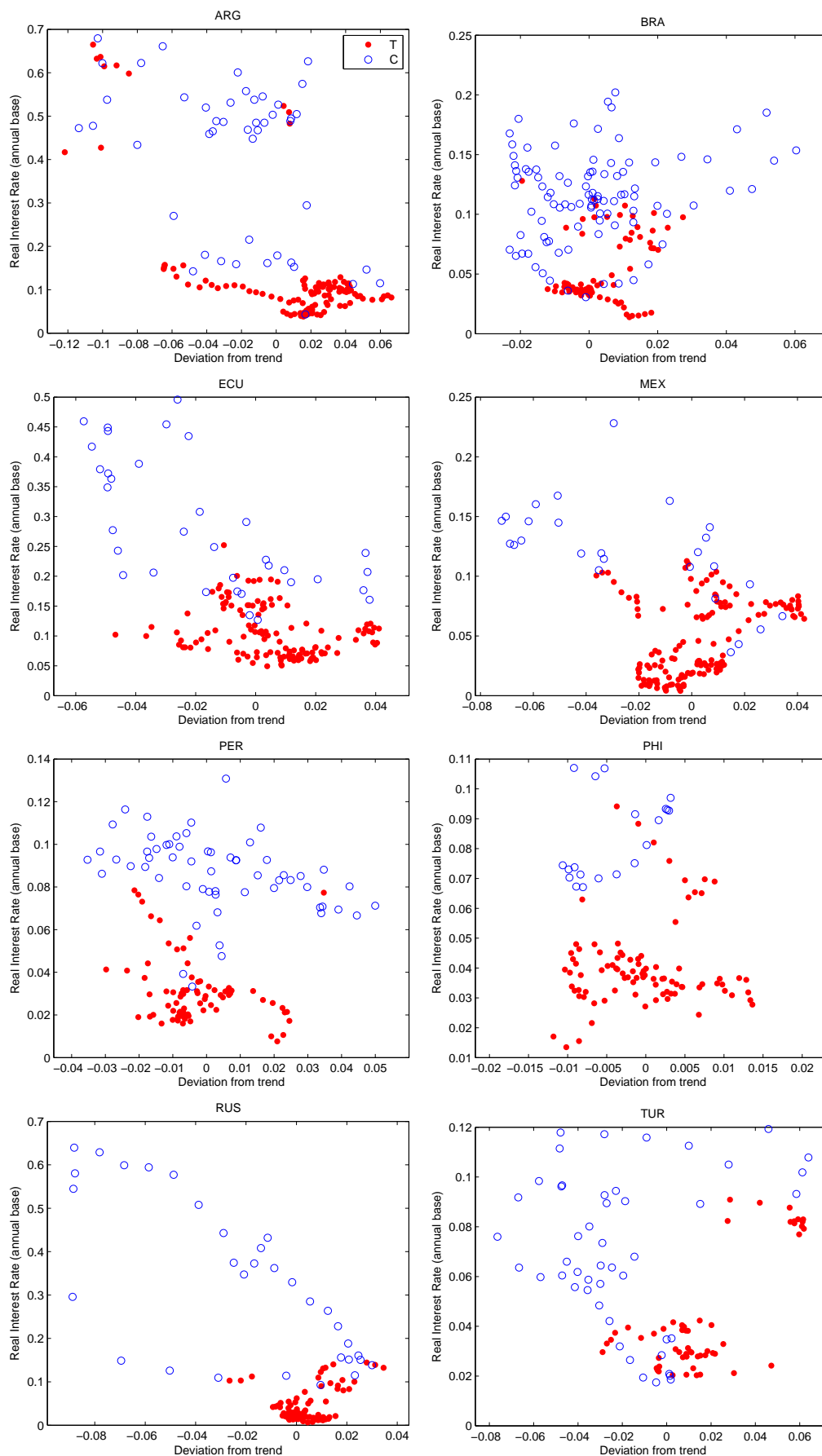
FIGURE 1.13: Real Interest Rate and HP filtered GDP.

The solid dots indicate observations for which the estimated smooth probability for

being in the Crisis regime for interest rates is less than 50%.
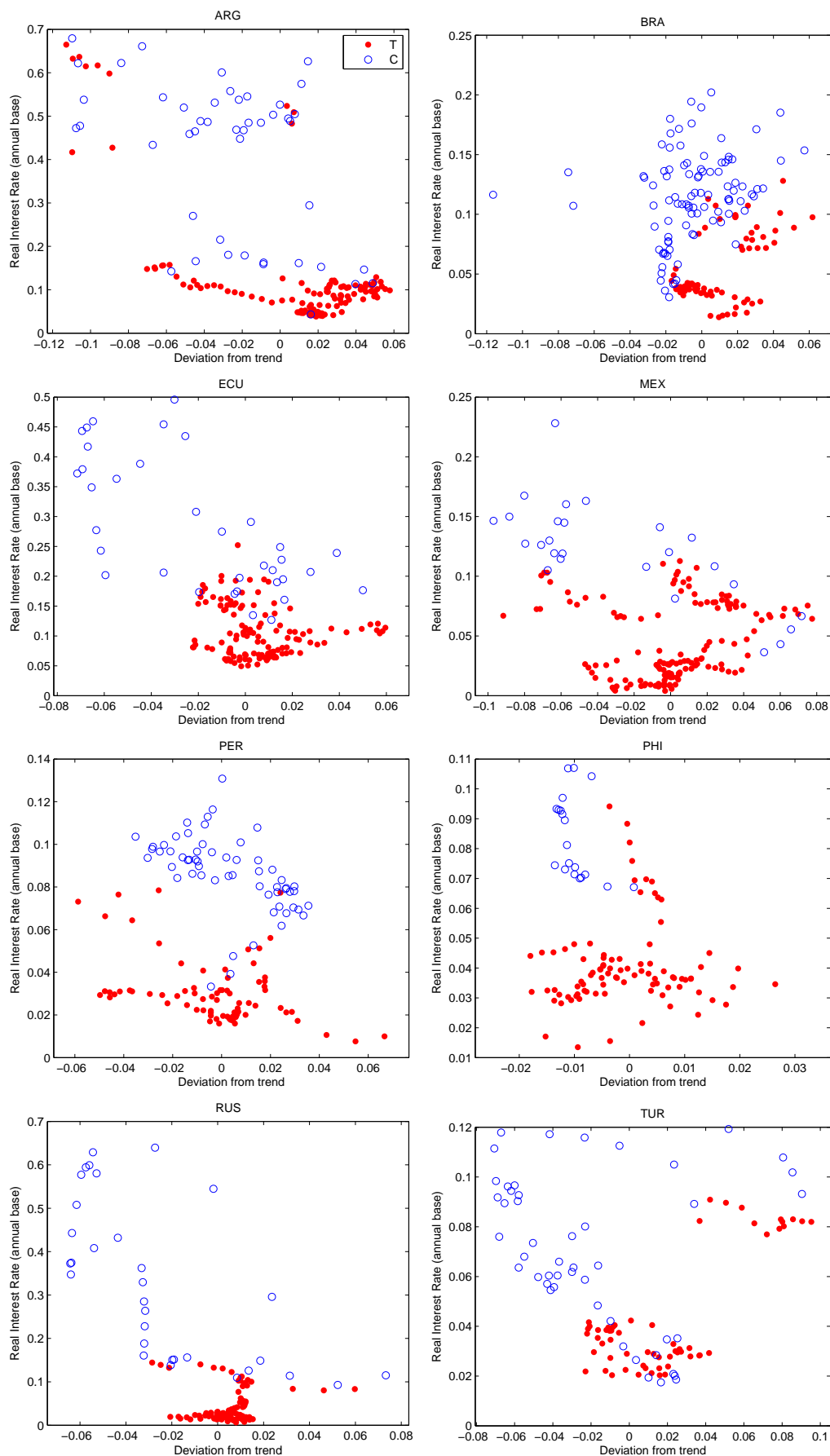
FIGURE 1.14: Real Interest Rates and HP filtered Consumption.

The solid dots indicate observations for which the estimated smooth probability for

being in the Crisis regime for interest rates is less than 50%.

Chapter 2

Regime Switching Interest Rates and Fluctuations in Emerging Markets[*]

Abstract

Many emerging economies have experienced current account reversals followed by large declines in economic activity. These sudden stops are reflected in their real interest rates, which alternate between tranquil times, when the level is relatively low and stable, and crises, during which interest rates are higher and more volatile. We embed an estimated regime switching process of interest rates into a small open economy model with financial frictions. Our model nests infrequent dramatic crises within regular business cycles, successfully matches the key second and higher order moments of the macroeconomic aggregates and produces plausible endogenous dynamics during crises. We find that the occurrence of sudden stops can account for the empirical regularities of emerging market business cycles. Financial frictions are essential for explaining emerging market fluctuations, but almost exclusively because of their effects in crises.

2.1 Introduction

Many emerging economies' business cycle fluctuations notably differ from those of developed small open economies: they are characterized by (1) a higher volatility of macroeconomic variables, (2) a strongly countercyclical trade balance, (3) consumption volatility exceeding output volatility, and (4) a real interest rate that is much more volatile in emerging economies, strongly countercyclical and leads the cycle.[1] Another characteristic of emerging economies is the occurrence of infrequent but traumatic current account reversals or sudden stops, followed by unusually large declines in economic activity. Given the prevalence of crises in the samples typically used in studies of emerging market fluctuations, it is not clear to what extent they are related to the salient features of the traditional business cycle moments in these countries.

In this chapter, we present a dynamic small open economy model that integrates infrequent sudden stops and regular business fluctuations and find that the potential for an abrupt and severe disruption in access to foreign lending can account for the empirical regularities of business cycles in emerging markets. Our analysis emphasizes the nonlinearities implied by the large but rare macroeconomic fluctuations following financial crises, and highlights the asymmetries these imply in the unconditional probability distributions of macroeconomic aggregates. We generate these asymmetries in the model by imposing a nonlinear exogenous process for interest rates: A key feature of real interest rate series for emerging economies is that they alternate between tranquil times, when the level is relatively low and stable, and more infrequent turbulent periods, during which the interest rate jumps to much higher and volatile levels. Our specification for the interest rate process is therefore based on empirical estimates from a Markov switching model.

The nonlinear nature of interest rates turns out to be important for the quantitative properties of otherwise conventional business cycle models. We focus on a version of the neoclassical small open economy model of Mendoza (1991) or Correia *et al.* (1995) with two main extensions: first, we include an intermediate input in the production process and assume a working capital constraint associated to the purchase of intermediate goods. Second, we allow for variable capacity

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[1]For a documentation of these regularities see, for instance, Neumeyer and Perri (2005) and Aguiar and Gopinath (2007).

utilization. We calibrate the model to Argentinean data, solve it using a global solution method and find it is successful in replicating the empirical regularities of business cycles in emerging markets. The model performs well not only in terms of matching the traditional second moments from data but also in terms of fitting the higher order moments of the main macroeconomic aggregates. In addition, the model produces plausible endogenous dynamics during crises, which are caused by a switch to a regime of high and volatile interest rates.

The quantitative success of the model relies importantly on three elements. The first is the nonlinear specification of the interest rate process. A switch to a regime of higher and more volatile interest rates is a clear mechanism generating sudden stops occurring with empirically plausible frequency. In addition, the asymmetric distribution of interest rates translates into skewed distributions for output, consumption and other macro aggregates that are very much as observed in Argentinean data. Other effects of the nonlinearity are more subtle and operate by affecting agents' precautionary savings motive. The quantitative exercises in Chapter 1 show that interest rates processes that display rare disaster states, as for instance discussed by Barro (2006), induce significantly less precautionary savings by optimizing agents than processes with symmetric distributions but identical first and second order unconditional moments. This implies that the specification for interest rates in small open economy models matters importantly for the vulnerability to unexpected drops in bond prices.

Whereas regime switching behavior is key in matching the second and higher order properties of the Argentinean data, we incorporate two further elements into the neoclassical model that improve its quantitative performance. Motivated by the countercyclicality of interest rates in emerging markets, Neumeyer and Perri (2005), Uribe and Yue (2006) and others have highlighted the role of domestic financial frictions for understanding their business cycles. Moreover, most of the literature on the dynamics of sudden stops has focused on credit frictions as propagation mechanisms (see for instance Calvo 1998, Christiano *et al.* 2004, Cook and Devereux 2006b,a, Gertler *et al.* 2007, Braggion *et al.* 2009). Given the importance of credit from suppliers as a source of short-term finance for firms, we assume a working capital friction linked to the purchase of intermediate inputs. Thus, changes in interest rates have direct effects on factor demands and production. Finally, we allow for variable capital utilization as an additional propagation

mechanism that, together with credit frictions, can account for the large drop in capacity utilization and the Solow residual during crises (see for instance Mendoza 2006 and Meza and Quintin 2007).

We use our calibrated model for Argentina to conduct a number of counterfactual experiments, which identify interest rate fluctuations as a major source of volatility. In our benchmark model, shutting down all interest rate shocks lowers volatility of output growth by more than half. However, it is almost exclusively the crises episodes that are responsible for this large effect. When we eliminate crises, but allow interest rate fluctuations as observed during tranquil times, the contribution of interest rate shocks to output growth volatility is an order of magnitude smaller. Other stylized facts of business cycles in emerging economies, such as the high relative volatility of consumption and countercyclicality of the trade balance, largely disappear when crises do not occur. Another implication regards the importance of domestic financial frictions for emerging markets: their role for explaining business cycle is limited to crises episodes. An alternative version of our model in which credit frictions are only active during crises performs at least as well as the benchmark model, in which strong credit frictions exist in every period.

The model in Mendoza (2010) shares with ours the emphasis on nesting infrequent crises within regular business cycle fluctuations and on the role of nonlinear dynamics. It incorporates many of the same elements, such as a working capital constraint, intermediate inputs and variable capacity utilization, but in addition introduces an occasionally binding collateral constraint. Sudden stops arise after a sequence of small shocks lead the economy to a region in the state space where this constraint becomes binding, triggering Fisherian debt deflation dynamics. In contrast to our analysis, Mendoza (2010) concludes based on a calibration to Mexican data that the occurrence of crises does not alter the business cycle moments significantly. The key reason for the divergent conclusions lies in the different precautionary savings behavior in both models. In Mendoza (2010), agents accumulate precautionary savings when approaching states in which the collateral constraint becomes binding. This lowers the vulnerability and decreases the probability of a severe crisis significantly. In our model, sudden stops are caused by an exogenous regime shift and, although agents are always rationally aware of possible disaster outcomes, crises take them by surprise when they materialize. The frequency and severity of crises follows primarily from the empirical estimates of the

regime switching model for interest rates. We acknowledge that some movements in the country risk component of interests rates are driven by changes in domestic fundamentals. Nevertheless, in many crises the size and speed of the reversal in capital flows and the rise in country spreads is largely unanticipated in light of recent domestic fundamentals.[2] Several empirical studies assign a limited role to innovations to domestic fundamentals in explaining changes in country spreads.[3] Also, the literature on early warning systems has found difficulties in identifying variables with reasonable predictive power for financial crises and their timing.[4] Therefore, viewing financial crises as being triggered by a (large) exogenous shock seems not only reasonable in many cases, but perhaps almost inevitable in the context of modern dynamic models with optimizing forward looking agents with strong self-insurance motives: Mendoza (2010) acknowledges that, with an endogenously binding collateral constraint, a realistic sudden stop does not occur in model simulations unless a sequence of favorable interest rate movements is reversed by a large negative shock, while simultaneously a large negative productivity shock materializes.

Our work is related to the broader literature on fluctuations in emerging economies, in particular to Neumeyer and Perri (2005), Uribe and Yue (2006) and Aguiar and Gopinath (2007). The main difference is that we emphasize nesting infrequent dramatic crisis events within regular business cycles. As crises in our model are associated with both a change in the level and the volatility of interest rates, this chapter is also related to the work of Fernández-Villaverde *et al.* (2009), who analyze the effect of volatility shocks to the interest rate in small open economy models. A key difference between our specification of the interest rate process and theirs is that the regime switching model combines both level and volatility shifts and captures the asymmetric alternation between tranquil and turbulent times.

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[2]Calvo *et al.* (2004) provide evidence of periods of sudden stops occurring simultaneously in a group of countries that were quite heterogenous in terms of fundamentals, suggesting contagion effects. According to the authors, it is hard to argue that there was a common deterioration of fundamentals driving these episodes, the only common link being that they were all emerging economies. Similarly, Kaminsky and Schmukler (1999) identify several episodes of extreme movements in financial markets during the 1997 East Asian crisis that cannot be linked to any substantial news about fundamentals, but seem to be caused by herding behavior of investors.

[3]See Uribe and Yue (2006), Longstaff *et al.* (2007) and González-Rozada and Levy Yeyati (2008).

[4]For example, Alvarez-Plata and Schrooten (2004) apply a prominent early warning system approach to the Argentinean experience and find that it did not give enough evidence for the 2001 crisis. They document that several leading indicators were even misleading during the immediate pre-crisis period.

Finally, this chapter is related to the literature that explores the transmission of sudden stops, such as Cook and Devereux (2006b,a), Gertler *et al.* (2007) and Braggion *et al.* (2009). While sudden stops are also driven by exogenous movements in real interest rates in these papers, the crisis shock is outside the set of realization that agents consider possible and is therefore not reflected in their behavior ex ante. Agents in our model are fully aware of the probability distribution of sudden stop events.

The rest of the chapter is structured as follows. In Section 2.2 we document the evidence for regime switching interest rates in a sample of emerging market economies and provide a numerical example that illustrates the effects of regime switching interest rates in dynamic stochastic general equilibrium models of small open economies. Section 2.3 describes the model we use for our empirical analysis and discusses its calibration to Argentinean data. In Section 2.4 we evaluate the model quantitatively and conduct a number of counterfactual experiments. Section 2.5 presents additional discussion of our modeling assumptions and draws some comparisons with related models in the literature. Finally, Section 2.6 summarizes our conclusions.

2.2   Evidence of Regime Switching Interest Rates

We begin by documenting the evidence for the regime switching behavior of interest rates for Argentina. For our purposes, the most relevant interest rate is the expected real borrowing rate faced by the domestic private sector, for which we need data on both private sector borrowing rates and expected domestic inflation. As Neumeyer and Perri (2005) argue, the high variability of inflation in emerging economies makes it extremely difficult to construct a reliable measure of expected inflation. In addition, private sector interest rates are not readily available for samples of sufficient size. Arellano and Kocherlakota (2008) and Mendoza and Yue (2008) report that sovereign interest rates and rates faced by firms in emerging economies are closely related; for Argentina, in particular, these studies report correlations above 0.8. We therefore follow Neumeyer and Perri (2005), Uribe and Yue (2006), Fernández-Villaverde *et al.* (2009) and others by constructing a domestic rate from a measure of the international risk free rate and data on sovereign bond spreads. We compute the sovereign bond quarterly average spread

for Argentina using the EMBI daily data reported by J.P.Morgan since December 1993, and extend the series backward relying on quarterly bond return data used by Neumeyer and Perri (2005). The international risk free real rate is obtained by subtracting the average year-on-year gross inflation of the U.S. GDP Implicit Deflator over the previous year from the annual yield on 3-month U.S. Treasury bills. Section 2.7.1 of the Appendix contains further details.
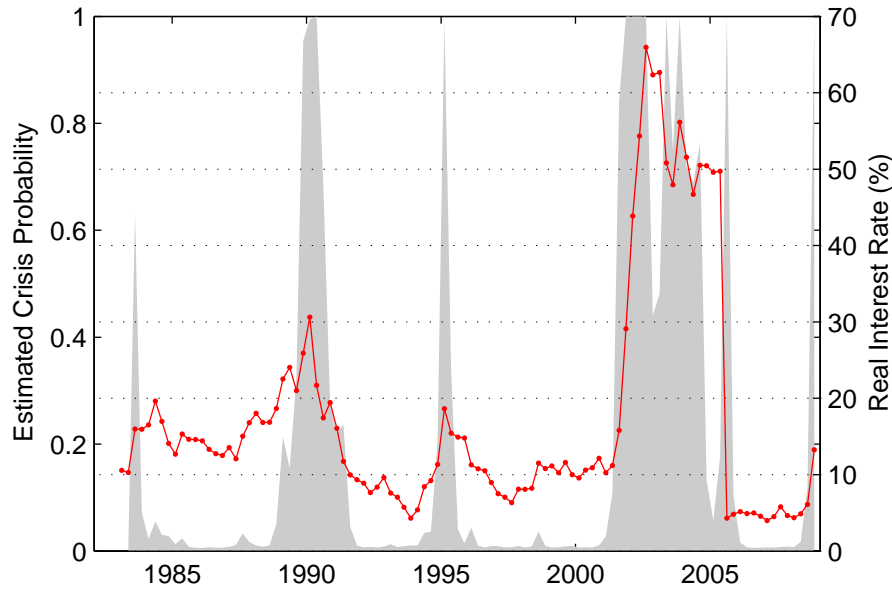
FIGURE 2.1: Real interest rate in Argentina (quarterly data). Grey areas denote estimated probability of the crisis state.

Figure 2.1 displays the extended quarterly real interest rate for Argentina; summary statistics and sample coverage are reported in Table 2.1.[5] The quarterly real interest rate for Argentina displays a similar pattern than the monthly sample of emerging economies analyzed in Chapter 1. It is clear to identify episodes in which the interest rate jumps to a much higher and more volatile level. These crisis episodes are also reflected in the sample statistics: not only is the sample standard deviations high (15.2%), the sample average is also considerably higher than the median (the sample mean is 17.6% while the sample median is 12.1%). Chapter 1 argued that simple linear models seem unlikely to be the best approximation of the interest rate dynamics faced by emerging economies and postulated the following Markov switching autoregressive model:

$$r_t = \nu(s_t) + \rho_r r_{t-1} + \sigma(s_t)\epsilon_t \quad , \quad \epsilon_t \sim \text{i.i.d } N(0,1) \tag{2.1}$$

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[5]The data on interest rates is expressed in annual basis.

where r_t is the real interest rate and ϵ_t is white noise. The state s_t is assumed to follow an irreducible ergodic two-state Markov process with transition matrix Π. This specification allows the intercept, $\nu(s_t)$, and the standard deviations of the statistical innovation, $\sigma(s_t)$, to be regime dependent, but assumes that the persistence parameter $0 \le \rho_r < 1$ is the same across regimes.[6] More precisely, $\nu(s_t)$ and $\sigma(s_t)$ are parameter shift functions stating the dependence of the parameters on the realization of one of two regimes, which we denote by C (crisis) and T (tranquil). There are therefore seven parameters to be estimated: ν_T, ν_C, ρ_r, σ_T, σ_C and two out of the four elements in the transition matrix Π.[7] We refer to Hamilton (1994) and Krolzig (1997) for details on the estimation of Markov switching models.

Table 2.1 shows the maximum likelihood estimates of the Markov switching model for the quarterly real interest rate in Argentina between 1983Q1 and 2008Q4. In the tranquil regime, the real interest rate averages 10.6% with a 1.7% standard deviation for the shocks. Instead, in the crisis regime the average is 47.3% and the standard deviation for the shocks is 12%. The tranquil regime is estimated to occur on average 77% of the time. Each quarter there is a 9% probability for Argentina of moving to the crisis regime. Once it enters the crisis regime, on average it stays there three to four quarters.

The estimated smooth probabilities of the crisis regime are shown as grey areas in Figure 2.1. The empirical model assigns significant crisis probabilities in all of the known turbulent periods in the sample: the end of the exchange rate stabilization plan in the first half of 1980s, the crisis-hyperinflation in the late 1980s and early 1990s, the aftermath of the 1994 Tequila crisis and the end of the convertibility plan (currency board), sovereign default and subsequent crisis in the last quarter of 2001. Also, the recent global financial crisis is reflected in the last two observations, 2008Q3 and 2008Q4. As a comparison, crisis indices in Calvo *et al.* (2004), Guidotti *et al.* (2004) and Rancière *et al.* (2008), which use data up to 2001, assign a crisis in Argentina (sudden stops, currency crises and/or banking

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[6]We also allowed for the persistence parameter to be regime dependent. However, based on results from a formal hypothesis test we could not reject the null hypothesis that the persistence parameter is the same across regimes. More precisely, we constructed a likelihood ratio test statistic and, since it has a nonstandard distribution due to a nuisance parameter problem, computed critical values by performing Monte Carlo simulations (2,000 repetitions). The p-value for the test statistic is 0.34.

[7]To be more precise, there is an additional parameter to estimate: the starting period state probability, which we estimate with the smooth probability for period one; see Hamilton (1990).

TABLE 2.1: Argentina Real Interest Rate: Summary Statistics and Markov-Switching Model Estimates (Quarterly Data).

Summary Statistics:

Sample	Q1/1983 Q4/2008
Observations	104
Min.	3.94%
Max.	65.95%
Mean	17.55%
Median	12.13%
Standard Deviation:	15.21%

Markov Switching AR Estimation:

Parameters:		$s_t = T$	$s_t = C$
Intercept	$\widehat{\nu}(s_t)$	0.39	1.73
		[0.4061]	[3.2577]
Autoregressive	$\widehat{\rho}_r$	0.9634	
		[0.0356]	
Unconditional Mean	$\widehat{\nu}(s_t)/(1-\widehat{\rho}_r)$	10.59	47.30
Standard Deviation	$\widehat{\sigma}(s_t)$	1.66	12.07
		[0.4647]	[5.9722]
Transition matrix	$\widehat{Pr}\{s_{t+1}=T|s_t\}$	0.91	0.32
		[0.046]	
	$\widehat{Pr}\{s_{t+1}=C|s_t\}$	0.09	0.68
			[0.3077]
Ergodic Probabilities		77%	23%

Linearity Test:		
	LR	61.81
	p-value	0.0001

Numbers in brackets are standard errors of estimates, computed with the Newey-West estimator. The p-value of the likelihood ratio statistic is obtained by Monte Carlo simulations (10,000 repetitions)

crises) in 1983-1984, 1989-1990, 1994-1995, 1999 and 2001. All of these periods show up in the shaded areas in Figure 2.1.

At the bottom of Table 2.1 we include the results from testing the hypothesis of a linear AR(1) against the alternative of the Markov switching model using a likelihood ratio test statistic. The value of the likelihood ratio for our sample is 61.35 while the 1% critical value is 22.35, so we can strongly reject the null hypothesis of linearity. The model in Equation (2.1) assumes that the autoregressive parameter

is the same across regimes. We have also tested this model against a more general specification in which the parameter might be different across regimes. More precisely, given the Markov switching specification $r_t = \nu(s_t) + \rho_r(s_t)r_{t-1} + \sigma(s_t)\epsilon_t$, the null hypothesis of the test assumes $\rho_r(T) = \rho_r(C)$. The p-value for the test statistic is 0.34, so we can not reject the null hypothesis that the autoregressive coefficient is equal across regimes.[8]

The results for Argentina quarterly real interest rate are reminiscent of the results shown in Section 1.2 of Chapter 1 for the monthly interest rate for a sample of emerging economies. Our conclusion is that, as for many other emerging economies, the quarterly real interest rate faced by Argentina between 1983Q1 and 2008Q4 can be characterized as alternating between a more frequent low level/low volatility regime and an infrequent high level/high volatility regime.

2.3   Model and Calibration

In this section, we present our benchmark model and discuss its calibration to Argentinean data. We also present some evidence to support our modeling assumptions of a credit friction associated with purchases of intermediate inputs and of variable capacity utilization.

2.3.1   The Model Environment

The model is that of a small open economy that faces stochastic shocks to productivity and the real interest rate, similar to Mendoza (1991), Correia *et al.* (1995) or Schmitt-Grohé and Uribe (2003). Both households and domestic firms trade a noncontingent real discount bond. As in Neumeyer and Perri (2005), Mendoza (2006) and Uribe and Yue (2006), the latter trade in the asset because of the presence of a working capital constraint: firms need to hold an amount of non-interest-bearing liquid assets equivalent to a fraction of their intermediate inputs purchases.

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[8]As pointed out by Hansen (1992) the likelihood ratio test statistic has a nonstandard distribution in this context due to a nuisance parameters problem. Accordingly, for both tests we computed critical values relying on Monte Carlo simulations (using 10,000 and 2,000 repetitions respectively).

Households and Preferences.   The economy is populated by identical, infinitely-lived households with preferences described by

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(c_t/\Gamma_t - \zeta\frac{h_t^{1+\psi}}{1+\psi}\right)^{1-\gamma} - 1}{1-\gamma} \quad , \quad 0 < \beta < 1, \gamma \geq 1, \psi \geq 0, \zeta > 0 \qquad (2.2)$$

where $c_t \geq 0$ denotes consumption and $h_t \geq 0$ is time spent in the workplace. The momentary utility function is of the form proposed by Greenwood *et al.* (1988). With this specification, labor supply depends only on the contemporaneous real wage. These preferences are popular in small open economy models because they generate more realistic business cycles moments (Correia *et al.*, 1995). They also facilitate our numerical solution procedure by eliminating a root finding operation. Households supply labor and capital services, receive factor payments and make consumption, saving and investment decisions. $\Gamma_t = g\Gamma_{t-1}$ measures the level of labor augmenting technology and enters utility to ensure balanced growth; $g \geq 1$ is the economy's average productivity growth factor. Households own a stock of capital $k_t \geq 0$, and provide capital services $k_t^s \geq 0$ equal to the product of the capital stock and the rate of capacity utilization $u_t \geq 0$. The households' budget constraint in period t is

$$c_t + x_t + d_t \leq R_t^{-1}d_{t+1} + w_t h_t + r_t^k u_t k_t \quad , \qquad (2.3)$$

where x_t are resources for investment and d_{t+1} is the households' foreign debt position in a one period noncontingent discount bond which is traded at price $1/R_t < 1$, r_t^k is the rental rate of capital services and w_t is the real wage. Long run solvency is enforced by imposing an upper bound on foreign debt, $d_{t+1} < \Gamma_t D$, precluding households from running Ponzi schemes. In practice, we set the value of D high enough such that this constraint never binds. We assume that $R_t = 1 + r_t$ when $d_{t+1} \geq 0$ where the interest rate r_t is given by (2.1). We also assume that if $d_{t+1} < 0$, i.e. if domestic households become creditors in international markets, the interest rate faced by the households is $R_t = \min\{1 + r_t, \bar{R}\}$ where $\bar{R} > 1$. Without this assumption, households have strong incentives to save and accumulate unrealistic amounts of bonds when the real interest rate jumps to crisis levels. In contrast, Argentina has always been a net debtor in our sample period: according to the data of Lane and Milesi-Ferretti (2007), the net foreign asset to GDP ratio from 1980 to 2004 has fluctuated between -9% to -72%. Although during the Argentinean crises domestic agents do increase saving, in practice they do so

by investing in very safe foreign assets, which pay a much lower interest rate than the borrowing rate faced by domestic households and firms. The upper bound on the return to international lending is intended to capture this feature.

The law of motion for capital is

$$k_{t+1} = x_t + \left(1 - \delta - \eta\frac{u_t^{1+\omega}}{1+\omega}\right) k_t - \frac{\phi_k}{2}\left(\frac{k_{t+1}}{gk_t} - 1\right)^2 k_t \ , \ \eta > 0 \ , \ \omega > 0 \ (2.4)$$

There is a quadratic capital adjustment cost and, as in Baxter and Farr (2005), the rate of capital depreciation depends positively on capital utilization.

The households' problem is to choose state contingent sequences of c_t, h_t, x_t, u_t, k_{t+1} and d_{t+1} to maximize expected utility (2.2), subject to the nonnegativity constraints, the budget constraints (2.3), the borrowing constraints and the law of motion for capital (2.4), for given prices w_t, r_t^k and R_t and initial values k_0 and d_0. The representative household's optimality conditions include:

$$\lambda_t = \frac{1}{\Gamma_t}\left(\frac{c_t}{\Gamma_t} - \zeta\frac{h_t^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{2.5}$$

$$\Gamma_t\zeta h_t^{\psi} = w_t \tag{2.6}$$

$$\eta u_t^{\omega} = r_t^k \tag{2.7}$$

$$\lambda_t = \beta\mathrm{E}_t\left[\lambda_{t+1}\right] R_t \tag{2.8}$$

$$\lambda_t\left(1 + \frac{\phi_k}{g}\left(\frac{k_{t+1}}{gk_t} - 1\right)\right) = \beta\mathrm{E}_t\left[\lambda_{t+1}\left(r_{t+1}^k u_{t+1} + 1 - \delta - \eta\frac{u_{t+1}^{1+\omega}}{1+\omega} + \frac{\phi_k}{2}\left(\left(\frac{k_{t+2}}{gk_{t+1}}\right)^2 - 1\right)\right)\right]$$
$$\tag{2.9}$$

Equation (2.5) defines the marginal utility of consumption. Equation (2.6) determines optimal labor supply, requiring that the marginal rate of substitution between leisure and consumption equals the real wage. Equation (2.7) determines the optimal capital utilization rate by equating the marginal cost of increased utilization due to higher depreciation to the rental rate of capital services. Equations (2.8) and (2.9) are the intertemporal Euler conditions determining the optimal portfolio allocation between bonds and capital.

Firms and Technology. At time t a representative firm rents capital services k_t^s and, in combination with labor input h_t and an intermediate input m_t, produces

z_t of a final good according to the production function

$$z_t = A_t \left[\mu^{1-\rho} m_t^\rho + (1-\mu)^{1-\rho} \left(\nu (k_t^s)^\alpha (\Gamma_t h_t)^{1-\alpha} \right)^\rho \right]^{\frac{1}{\rho}} \tag{2.10}$$

$$\Gamma_t = g\Gamma_{t-1} \ , \ 0 < \alpha < 1 \ , \ 0 \le \mu < 1 \ , \ \rho < 1, \nu > 0 \ . \tag{2.11}$$

where A_t is the stochastic level of productivity. The firm is entirely owned by domestic households and all factor markets are perfectly competitive. Both intermediate and final goods are traded internationally. Whether the intermediate good is being produced domestically or is imported from abroad is irrelevant and, for simplicity, we assume that the relative price of the intermediate input in terms of the final good is unity.[9] As in Uribe and Yue (2006), production is subject to a financing constraint requiring final goods producing firms to hold an amount κ_t of a non-interest bearing asset as collateral. We assume that κ_t must be a proportion $\varphi \ge 0$ of the cost of the intermediate good inputs:

$$\kappa_t \ge \varphi m_t \tag{2.12}$$

The representative firm's distribution of profits at period t is $\pi_t = z_t - w_t h_t - r_t^k k_t^s - m_t - \kappa_t + \kappa_{t-1}$. The firm's problem is to choose state contingent sequences for k_t^s, h_t, m_t and κ_t in order to maximize the present discounted value of expected profits distributed to the households:

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \pi_t \ , \tag{2.13}$$

subject to the financing constraints in (2.12) and taking as given all prices w_t, r_t^k and the representative household's marginal utility of consumption, λ_t in (2.5). The representative firm's optimality conditions include (2.8) and:

$$A_t^\rho (1-\mu)^{1-\rho} \left(\frac{z_t}{f_t} \right)^{1-\rho} \alpha \frac{f_t}{k_t^s} = r_t^k \tag{2.14}$$

$$A_t^\rho (1-\mu)^{1-\rho} \left(\frac{z_t}{f_t} \right)^{1-\rho} (1-\alpha) \frac{f_t}{h_t} = w_t \tag{2.15}$$

$$A_t^\rho (\mu)^{1-\rho} \left(\frac{z_t}{m_t} \right)^{1-\rho} = 1 + \varphi \left[\frac{R_t - 1}{R_t} \right] \tag{2.16}$$

where $f_t = \nu (k_t^s)^\alpha (\Gamma_t h_t)^{1-\alpha}$. Equations (2.14) to (2.16) determine the firms' factor demands. It is clear from equation (2.16) that the working capital constraint

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[9]An alternative assumption is that the relative price is an exogenous random variable. In that case, fluctuations in this price are isomorphic to fluctuations in A_t.

introduces a wedge between the marginal product of intermediate inputs and its relative price (which is constant and equal to one). This distortion increases in the opportunity cost of working capital for firms, $(R_t - 1)/R_t$, and in the strength of the financial friction, φ.

Equilibrium   An equilibrium is a set of infinite sequences for prices r_t^k, w_t and allocations c_t, h_t, x_t, u_t, m_t, κ_t, k_{t+1}, d_{t+1} such that households and firms solve their respective problems given initial conditions k_0 and d_0 for given sequences of A_t and R_t, and labor, asset and goods markets clear. A balanced growth equilibrium is an equilibrium where c_t/Γ_t, h_t, x_t/Γ_t, u_t, m_t/Γ_t, k_{t+1}/Γ_t, d_{t+1}/Γ_t are stationary variables. Henceforth, we denote the detrended variables by a hat (optimality conditions expressed in terms of the detrended variables are shown in Appendix 2.7.3). Using equations (2.14) to (2.16), Appendix 2.7.2 shows how detrended GDP $(\hat{y}_t = r_t^k u_t \hat{k}_t + \hat{w}_t h_t)$ in equilibrium can be expressed as:

$$\hat{y}_t = \mathcal{A}_t(A_t, q_t) \left(u_t \frac{\hat{k}_t}{g} \right)^\alpha h_t^{1-\alpha} \tag{2.17}$$

$$\mathcal{A}_t(A_t, q_t) = \nu \left(\frac{A_t^{\frac{\rho}{\rho-1}} - \mu \left(1 + \varphi q_t\right)^{\frac{\rho}{\rho-1}}}{1 - \mu} \right)^{\frac{\rho-1}{\rho}} \tag{2.18}$$

where $q_t = (R_t - 1)/R_t > 0$. We denote the term $\mathcal{A}_t(A_t, q_t)$ as "measured" TFP , which corrects for capital utilization but is still affected by the distortion introduced by the working capital constraint. An increase in R_t raises q_t, the opportunity cost of funds for the firm, and lowers $\mathcal{A}_t(A_t, q_t)$. A smaller elasticity of substitution $1/(1-\rho)$ between intermediate inputs and value added and a higher value of φ both magnify the negative effect of interest rates on total factor productivity. The market clearing conditions are

$$\hat{z}_t - \hat{m}_t \left(1 + \varphi q_t\right) = \hat{y}_t \tag{2.19}$$

$$\hat{c}_t + \hat{x}_t + \hat{nx}_t = \hat{y}_t \tag{2.20}$$

where $\hat{nx}_t$ are (detrended) net exports, given by $\hat{nx}_t = \hat{d}_t/g - R_t^{-1}\hat{d}_{t+1}$. The household's debt position $\hat{d}_t$ is the economy's net foreign debt position in period t, and the trade balance, or net exports, are all resources not used for consumption and investment.

2.3.2 Evidence on Modeling Assumptions

This section discusses the empirical motivation for two features of the model: the credit friction associated with intermediate inputs and variable capacity utilization. We assume that firms need intermediate inputs for production and that a fraction of its payment entails a financial cost.[10] There is broad evidence indicating that the trade of intermediate inputs between firms often entails some sort of financial arrangement, both when it refers to domestic or to foreign suppliers. Petersen and Rajan (1997), for example, signal trade credit as the single most important source of short-term funding for firms in the US, and that its importance is greater for firms that have less access to financial institutions. Reliance on credit from suppliers might be even more important in developing economies, given the lower development of the financial sector.[11] Regarding the relationship with providers across borders, the existence of financial costs linked to the purchase of inputs is even more common: Auboin (2009) signals that 80% to 90% of world trade relies on trade finance (trade credit and insurance/guarantees), mostly of a short-term nature.

Evidence from periods of financial instability in emerging markets suggests that reductions in trade credit are an important transmission mechanism through which financial shocks affect the real economy.[12] Figure 2.2 shows a very close correlation between the drop in total loans to the private sector, imported intermediate inputs and GDP during the 2001 crisis in Argentina. Energy consumption, an indirect measure of materials use, shows a sharp drop around the crisis. According to the International Monetary Fund (2003), trade credit declined 30%-50% in Brazil and Argentina during the 2001-2002 crisis and 50% in Korea in 1997-1998, maturities were drastically reduced and the financial cost of these credits increased significantly. Auboin and Meier-Ewert (2003) argue that the credit crunch in trade finance also affected "domestic" trade credit in general in Argentina and other countries.

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[10]Other examples in the literature of this assumption include Christiano *et al.* (2004), Mendoza and Yue (2008), Braggion *et al.* (2009) and Mendoza (2010).

[11]In Mexico, for example, more than 65% of firms have stated credit from suppliers as the main source of credit on average from 1998 to 2009 (survey results, "Encuesta de Evaluación Coyuntural del Mercado Crediticio", Central Bank of Mexico).

[12]See Auboin and Meier-Ewert (2003), International Chamber of Commerce (2008), Braggion *et al.* (2009) and International Monetary Fund (2003, 2009a,b) for further reference.
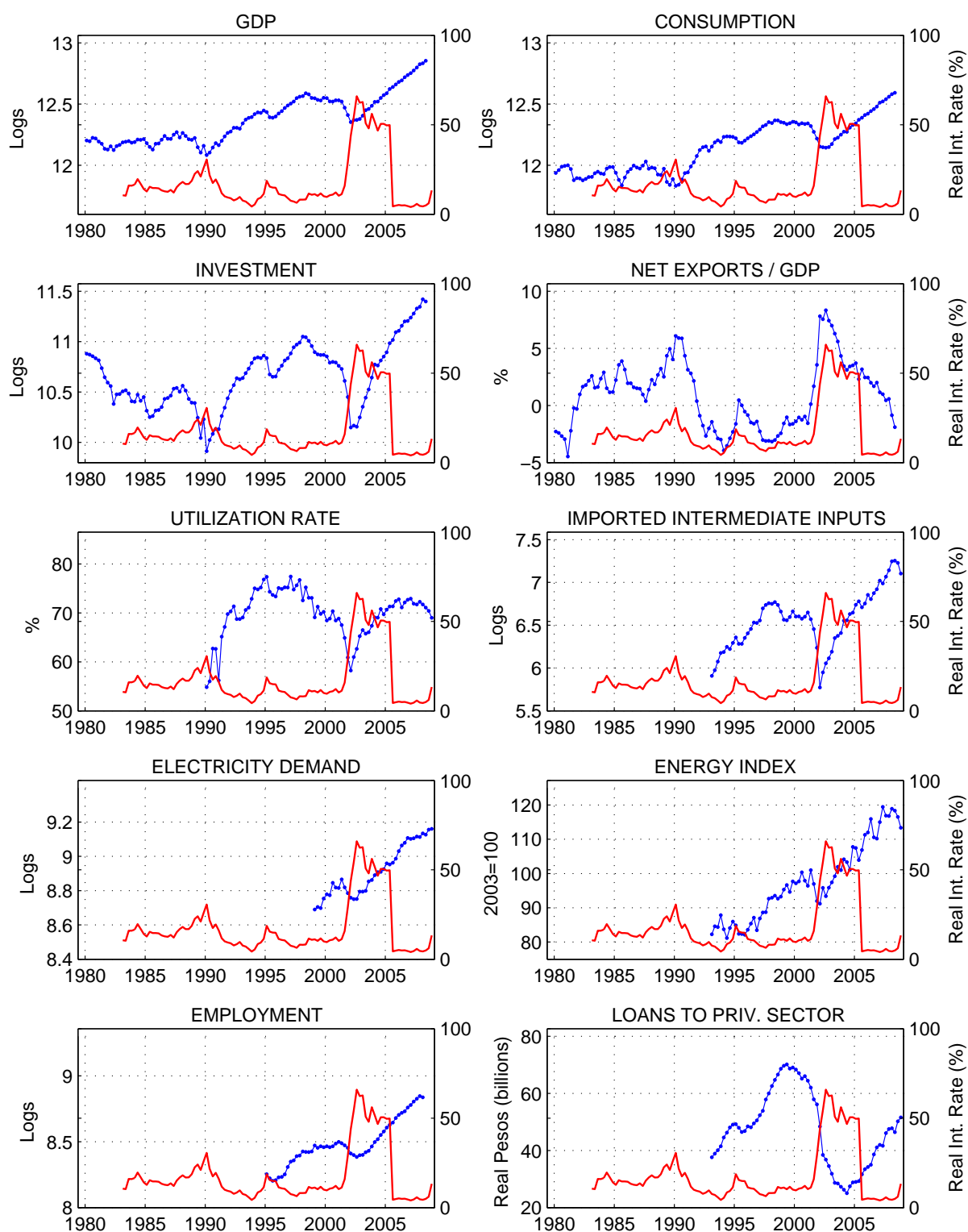
FIGURE 2.2: Main macroeconomic variables for Argentina.

Finally, some evidence suggests that there is a shift from open account arrangements between trade partners to cash-in-advance or to bank intermediated transactions during financial crises and that there is an increase in the fraction of trade credit backed up by collateral; see International Chamber of Commerce (2008) and Braggion *et al.* (2009). This motivates a later extension of the model in Section 2.5.1.

As in Meza and Quintin (2007), we allow for variable capital utilization in our model. The utilization rate in Argentina shows important variations over time and seems to have played a relevant role in the adjustment of the Argentinean economy during the major crises. Figure 2.2 shows that the utilization rate fell significantly during the 2001 crisis. Available data starts only on 1990Q1, but the low utilization rate at the beginning of the sample suggests that it also played a relevant role during the 1989 crisis.

2.3.3   Calibration and Solution Method

We calibrate the model to Argentinean quarterly data from 1980Q1-2008Q2. Appendix 2.7.1 provides more detail on data sources and transformations. Besides the parameters of the interest rate shock process, there are 17 parameters in the model. For 11 of those parameters (α, β, δ, η, ζ, ν, μ, ϕ_k, $\bar{R}$, g, σ_a), we calibrate the values to match data on the basis of moments of the ergodic distribution implied by the nonlinear solution of the model. In the case of trending variables, the moments used for calibration are from year on year growth rates. For 5 parameters ($\gamma, \psi, \omega, \rho_A, \rho$), the values are harder to pin down directly from the data, and we chose values we believe are most common in the literature. The remaining parameter, φ, which determines the strength of the financial friction, is very important for the empirical success of the model as pointed out by Neumeyer and Perri (2005). For now we set $\varphi = 1$, such that the required working capital equals the total cost of intermediate good purchases, and we will devote Section 5.1 to a discussion of this assumption.

Preference parameters   The moment utility and labor curvature parameters are fixed to $\gamma = 2$ and $\psi = 0.6$, which are the values in Mendoza (1991), Aguiar and Gopinath (2007) and others. The discount factor β is set to match the average

trade balance to GDP ratio in Argentina of 1.1% during 1981Q1 to 2008Q2. The implied average debt to GDP ratio is about 50%.[13] The labor weight ζ matters only for scaling and normalizes the average labor input to approximately one.

TABLE 2.2: Calibration, Benchmark Model

a) Preferences	Symbol	Value	Target
Discount factor	β/g	0.9598	Trade balance to GDP ratio
Utility curvature	γ	2	Mendoza (1991), ...
Labor disutility weight	ζ	0.62	Normalized labor input
Inverse wage elasticity of labor supply	ψ	0.6	Mendoza (1991), ...
b) Technology			
Capital income share	α	0.38	Labor income share
Scaling parameter	ν	0.57	normalized GDP
Intermediate inputs weight	μ	0.44	IO table
Growth factor	g	1.0083	Average output growth
Production substitution elasticity	$1/(1-\rho)$	0.0001	Rotemberg and Woodford (1996)
Working capital requirement	φ	1	See Section 5.1
Capital depreciation parameter 1	δ	-0.017	I-Y ratio, normalized utilization rate
Capital depreciation parameter 2	η	0.081	I-Y ratio, normalized utilization rate
Capital depreciation parameter 3	ω	0.44	Meza and Quintin (2007), utiliz. rate
Capital adjustment cost	$\phi_k/2$	19.3	Relative investment volatility
Saving interest rate ceiling	$\bar{R}$	$1.02^{0.25}$	International riskless rate
c) Technology Shock Process			
Persistence of TFP shock	ρ_A	0.95	Neumeyer and Perri (2005)
Standard deviation of TFP shock	σ_A	0.0027	Output volatility
d) Interest Rate Shock Process			

See Table 2.1.

Technology parameters. The quarterly growth rate $g-1$ is 0.83%, the average quarterly growth rate of output in Argentina in the sample, excluding the crises after 1989Q1 and 2001Q2 (see Appendix 2.7.1). The parameter α is set to obtain a labor income share of 0.62 as in Mendoza (1991), Aguiar and Gopinath (2007) or

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[13]Expressed in terms of annual GDP, the average debt to GDP ratio in the model is 12.5%. The average net foreign asset to GDP ratio between 1980 and 2004 in the data of Lane and Milesi-Ferretti (2007) is -36.5%. In the model the only asset is a one-period bond and there is no default, which makes it impossible to match both the average trade balance to GDP and debt to GDP ratios in the data at the same time.

Neumeyer and Perri (2005). The value of μ matches the 44.2% share of intermediate goods consumption in gross output in Argentina's 1997 input-output matrix. We assume very little possibility to substitute away from material inputs and set the elasticity of substitution $1/(1-\rho)$ to a very low number, as in Rotemberg and Woodford (1996). There is no evidence on this elasticity for Argentina. Estimates for the US surveyed in Bruno (1984) suggest a range between 0.3 and 0.4, but Basu (1996) considers this an upper bound. In Section 4.2 we do a sensitivity check that suggests the low elasticity we assume is not too essential for our results.

The depreciation parameters δ and η are set to normalize the rate of capital utilization and to match the average investment-output ratio in Argentina of 18.2%. The resulting quarterly depreciation rate is about 3.7% on average. The parameter ω, which determines the elasticity of the depreciation rate with respect to variations in capital utilization, is set to 0.44, the value in Meza and Quintin (2007).[14] For this value of ω, the volatility of the utilization rate happens to coincide with the volatility of the quarterly series of capacity utilization rate in Argentina (available only from 1990 onwards). The capital adjustment cost parameter ϕ_k matches the volatility of investment in the data. We posit an autoregressive process for technology:

$$\ln(A_t) = \rho_A \ln(A_{t-1}) + \sigma_A \epsilon_{A,t} \ , \ \ \epsilon_{A,t} \sim \text{i.i.d } N(0,1) \qquad (2.21)$$

with $\rho_A = 0.95$, as in Neumeyer and Perri (2005), and σ_A matching the volatility of output.[15]

Real Interest Rates   The interest rate process is the estimated regime switching model for Argentina, with parameters given in Table 2.1 and $\bar{R}$ set to $1.02^{0.25}$, the average real rate on a US 3-month Treasury-bill.

Numerical Solution   We compute discrete approximations to the stochastic processes for technology and the interest rate. The technology process in (2.21) is

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[14]The value is not entirely comparable to Meza and Quintin (2007) because of slightly different parametrization of the depreciation function. Our specification allows us to match the investment-output ratio, but the depreciation elasticity is not constant and depends on u_t.

[15]This is also the procedure adopted in Neumeyer and Perri (2005), among others, since labor statistics in Argentina do not allow to estimate a reliable series for Argentina's Solow residuals with quarterly frequency.

approximated using the quadrature-based method of Tauchen and Hussey (1991) on a grid of 11 nodes. We approximate the Markov switching process for the interest rate in (2.1) on a grid of 51 equidistant nodes. To facilitate the numerical solution procedure, our approximation of the interest rate process imposes that innovations are drawn from normal distributions that are truncated to ensure that the annualized net interest rate has a support bounded between 0% and 100%. To guarantee a satisfactory approximation to the Markov switching model estimated from the data, we follow a simulated method of moments procedure: For given parameters $\Theta = [\nu(s_t), \sigma(s_t), vec(\Pi), \rho_r]$, we obtain the discrete approximation, simulate 52,000 observations and construct $\tilde{\Psi}(\Theta) = [\tilde{\nu}(s_t), \tilde{\sigma}(s_t), vec(\tilde{\Pi}), \tilde{\rho}_r, \tilde{\mu}_r, \tilde{\sigma}_r]'$ where $\tilde{\nu}(s_t), \tilde{\sigma}(s_t), vec(\tilde{\Pi})$ and $\tilde{\rho}_r$ are the Markov switching model estimates and $\tilde{\mu}_r$ and $\tilde{\sigma}_r$ are the average unconditional sample mean and standard deviation over samples of the same length as the data. Finally, we find Θ that minimizes the loss function $\left[\tilde{\Psi}(\Theta) - \hat{\Psi}\right]' W \left[\tilde{\Psi}(\Theta) - \hat{\Psi}\right]$ where $\hat{\Psi}$ is a vector stacking the parameters estimated from the data and W is a diagonal weighting matrix containing the inverses of the variances of the parameter estimates. Figure 2.3 depicts the density of the Argentinean interest rate and the density implied by our discrete approximation to the process.
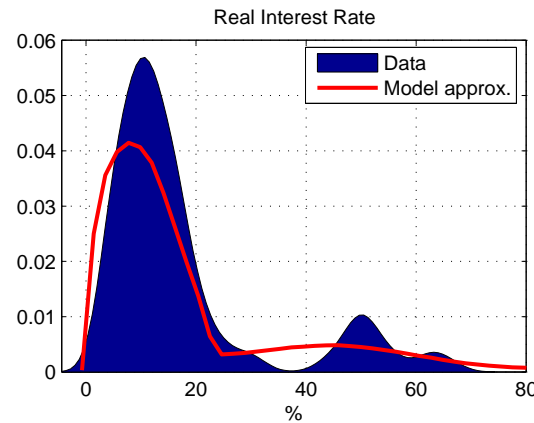
FIGURE 2.3: Distribution of the real interest rate in data and implied by the discrete approximation used in the model.

We approximate the policy functions for the state variables $\hat{d}_{t+1}$ and $\hat{k}_{t+1}$ by piecewise linear functions over a grid and compute the approximate solution by iterating over the intertemporal Euler conditions, as suggested by Coleman (1990). The standard iteration procedure is generally slow and therefore we combine it with the method of endogenous gridpoints, proposed by Carroll (2006). The lack of any wealth effects on labor supply implies that there are no numerical rootfinding

operations required in the algorithm. The details are presented in Appendix 2.7.3 and Matlab programs are available on the authors' websites.

2.4   Quantitative Model Analysis

Before turning to the numerical results, it is instructive to give some intuition behind the model response to the exogenous disturbances driving aggregate fluctuations: technology shocks, interest rate shocks and shifts in the volatility of interest rates.

The effects of technology and interest rate shocks in the standard small open economy model are relatively well understood. A positive and transitory shock to technology increases labor demand which, depending on the elasticity of labor supply, induces an increase in employment and production; see for instance Mendoza (1991) or Correia *et al.* (1995). The increase in current and future expected real income raises consumption, but as the productivity boom is transitory, households also respond by saving more. The increase in saving boosts investment in domestic capital and lowers debt to foreigners. On the other hand, households take advantage of higher productivity in domestic production and shift resources towards domestic investment, increasing foreign borrowing. The net effect on the trade balance depends on the model specifics and calibration. In our case with variable capital utilization and persistent technology shocks, the net effect is a positive comovement between output and the trade balance.

The main effect of an interest rate increase in the standard model is a shift away from domestic investment and a reduction of foreign debt. A reduction in wealth induces a drop of consumption, but there is generally little contemporaneous effect on output or labor supply. Because of the financial constraint in our model, however, there are additional effects through an increase in the financing distortion. Higher interest rates cause a rise in the relative cost of intermediate inputs which in turn lowers the marginal product of both labor and capital services. From equation (2.18), it is clear that this additional effect is isomorphic to a negative technology shock. The regime switching nature of the interest rate, however, implies very persistent drops in the marginal product of labor and capital when the

economy moves to the crisis regime. Given the variable rate of capacity utilization, capital services respond immediately to the drop in marginal productivity, which, together with a reduction in labor input, contributes to an immediate drop in production. As a result, interest rate shocks yield comovement between output, investment and consumption, but unlike technology shocks, they also yield consumption responses that exceed those of output and a negative comovement between output and the trade balance.

The dynamics in the model are governed not only by shocks to the levels of technology and interest rates, but also by shifts across tranquil and crisis regimes. A transition to a crisis is characterized by increases in the level as well as the volatility of interest rates. As shown by Fernández-Villaverde *et al.* (2009), these volatility shifts have important distinct effects. An increase in the relative risk of foreign bonds induces households to reduce foreign indebtness, which requires a reduction in consumption. During crises, the returns on capital investment and bonds are more highly correlated as interest rate fluctuations become more dominant in determining factor productivities. The increased risk discourages investment and a lower capital stock in turn decreases labor input and production. Shifts in interest rate volatility contribute to a negative comovement between output and the trade balance.

2.4.1   Business Cycle Statistics

All three sources of fluctuations generate comovement between output, consumption, investment and hours worked, and are therefore candidates for explaining a substantial fraction of aggregate fluctuations. However, the relative importance of technology shocks, interest rate shocks as well as the frequency of crises determines the relative volatility of consumption, the correlation of the trade balance with output as well as the unconditional correlations of interest rates with output.

Table 2.3 contains simulated moments based on the benchmark calibration of the model. The first column contains the key business cycle statistics in the 1980Q1-2008Q2 sample of Argentinean quarterly data. The second column contains the corresponding moments in model simulated data, obtained by generating 1000 samples of the same size as the actual data, each with a burn-in of 1000 quarters.

TABLE 2.3: Simulation Results: Year on Year Growth Rates

		Data	Benchmark	No Crises	Tech Shocks Only
a) Standard Deviations					
Output (T)	$std(g_y)$	0.065	0.065	0.032	0.028
			(0.044,0.086)		
Consumption	$std(g_c)/std(g_y)$	1.14	1.10	0.83	0.75
			(0.94,1.25)		
Investment (T)	$std(g_x)/std(g_y)$	3.14	3.14	2.59	1.75
			(2.68,3.62)		
Trade balance to GDP	$std(nx/y)$	0.029	0.032	0.010	0.003
			(0.021,0.042)		
b) Cross-Correlations with g_y					
Consumption	$corr(g_c, g_y)$	0.94	0.95	0.96	0.99
			(0.92,0.97)		
Investment	$corr(g_x, g_y)$	0.92	0.94	0.94	0.99
			(0.91,0.96)		
Trade balance to GDP	$corr(nx/y, g_y)$	−0.30	−0.52*	−0.12	0.70
			(-0.66,-0.36)		
c) Cross-Correlations with R					
Output	$corr(g_y, R)$	−0.21	−0.45*	−0.28	0
			(-0.59,-0.31)		
Consumption	$corr(g_c, R)$	−0.26	−0.40	−0.36	0
			(-0.56,-0.25)		
Investment	$corr(g_x, R)$	−0.07	−0.32*	−0.32	0
			(-0.47,-0.17)		
Trade balance to GDP	$corr(nx/y, R)$	0.71	0.68	0.91	0
			(0.37,0.88)		

(T) denotes that the statistic was targeted in the calibration. Numbers in parenthesis are 10% and 90% quantiles. An asterisk in the second column denotes that the corresponding data moment does not lie within these quantiles.

The table also reports the 10% and 90% quantiles of the simulated sample moments. The moments are for the year on year growth rates of output, consumption and investment as well as the trade balance to GDP ratio. As a reference, a table in the appendix reports the moments when either a linear trend or the HP filter is used.[16]

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[16]The data moments targeted in the calibration are always in terms of annual growth rates of the variables. Some moments in the data are sensitive to the detrending method.

Consumption Volatility   Recalling that the volatility of the growth rates of output and investment are matched by construction in the calibration, we first highlight the fact that the model is successful in producing a relative volatility of consumption that is in line with the data. The model moment averages 1.10, very close to value in data, which lies comfortably within the 10% and 90% quantiles of simulated moments. As suggested before, the nonlinearity in interest rates tends to magnify consumption volatility: On the one hand, the self-insurance motive is less strong compared to models where interest rates are relatively volatile all the time. On the other hand, unexpected movements in wealth induced by changes in interest rate are more infrequent, but at the same time much larger and therefore generate stronger consumption responses. In addition, changes in the volatility of interest rates also translate into higher consumption volatility.

Countercyclical Trade Balance   The model does very well in reproducing a strongly countercyclical trade balance: the correlation between output growth and the trade balance to GDP ratio is -0.53 in the model, whereas in the data it is -0.30 which is slightly above the 90% quantile of simulated moments. Even though the precise number in the data is somewhat sensitive to the detrending method, the negative correlation produced by our model is nevertheless high. For comparison, the correlation is much more pronounced than in the model specification of Neumeyer and Perri (2005) that, as in our model, assumes independent interest rate and productivity shocks.[17] Again, the difference depends importantly on the regime switching behavior of interest rates, as suggested by our earlier example and as evidenced further below.

Cyclicality of Interest Rates   The correlations between output and consumption on the one hand, and real interest rates on the other hand are all negative in the data. The correlation between investment and interest rates is close to zero when we use growth rates. The model is successful in reproducing the countercyclical properties of real interest rates: the average sample correlation is -0.45. It

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[17]The model specification in Neumeyer and Perri (2005) with independent processes for interest rates and productivity shocks is the closest to our model. Their preferred specification, instead, assumes that interest rates (or their spread component) is a function of expected productivity. We have no evidence to assume such a structural dependence. Moreover, some empirical estimations suggest that the role of innovations to domestic fundamentals in explaining fluctuations in spreads is limited (see, for example, Uribe and Yue (2006), Longstaff *et al.* (2007) and González-Rozada and Levy Yeyati (2008)). Accordingly, we assume both processes to be independent.

somewhat overstates the negative contemporaneous correlation between the real interest rate and output: the moment in the data lies above the 90% quantile. Neumeyer and Perri (2005) show not only that interest rates are countercyclical in emerging markets, but also that interest rates lead the cycle. Figure 2.4 plots the cross-correlations between interest rates and output growth at different leads and lags for Argentinean data: The model accurately matches the inverse S-shape of the cross correlations between output growth and real interest rates. The average sample correlation between consumption and interest rates is -0.40. The moment in the data is somewhat higher but lies within the 10% and 90% quantiles of simulated sample moments. In the case of investment the average sample correlation with the interest rate is somewhat below the data counterpart (the moment in the data is, however, strongly negative when using alternative detrending methods). The model performs well in matching the correlation of the trade balance with interest rates. The sample average of the correlation is 0.68, very close to the 0.71 correlation in the data.
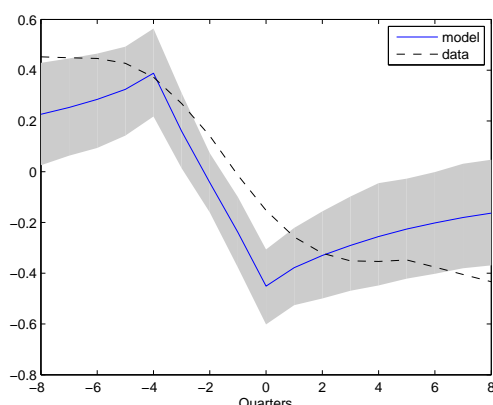
FIGURE 2.4: Cross-correlations between GDP growth at various leads and lags, and interest rates. The grey area indicates the region in which 80% of the simulated sample moments lie.
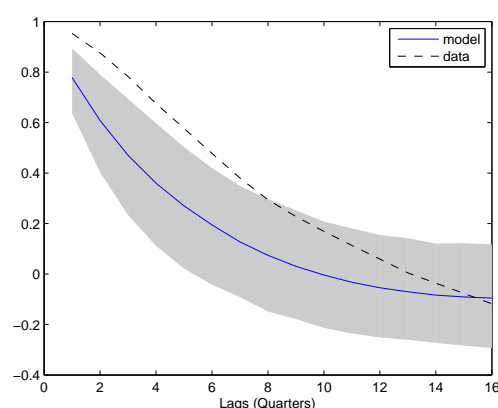
FIGURE 2.5: Autocorrelation function of the trade balance to GDP ratio. The grey area indicates the region in which 80% of the simulated sample moments lie.

The Persistence of the Trade Balance Figure 2.5 depicts the autocorrelation function of the trade balance to GDP ratio, both in Argentinean data and the model generated samples. García-Cicco *et al.* (2010) show how the standard small open economy RBC model with only temporary and permanent technology shocks predicts a nearly flat autocorrelation function for the trade balance. From the empirical evidence in their paper, as well as from Figure 2.5, it is clear that

this prediction is strongly counterfactual for Argentina: the autocorrelations are all significantly below one and converge to zero relatively quickly as the number of lags increases. Figure 2.5 shows that the model with interest rate shocks is successful in replicating the autocorrelation function.

2.4.2   Crisis Dynamics

In terms of the second order moments the model is relatively successful in matching the Argentinean experience. We now explore the ability of the model to account for the behavior of macroeconomic aggregates in Argentina during times of financial crisis. First, we present the responses of macro-aggregates in the model around sudden stop episodes and compare them with two actual episodes. Second, we investigate the predictions of the model conditional on the observed series for the real interest rate. Finally, we look at the higher order moments.

Sudden Stops   Figure 2.6 plots the model response of output, consumption, investment and the trade balance during a sudden stop.[18] The graph also depicts the path of the variables during two crises in the sample, which we date using the estimated crisis probabilities from the regime switching model. The first crisis has a zero date of 1989Q1 after which, as is clear from Figure 2.1, the estimated crisis probabilities is elevated for around 6 quarters. The second crisis has a zero date of 2001Q2 after which the estimated crisis probabilities remain very high for almost four years. In the graph, the economy enters the crisis regime in period 1 and the responses are the averages over the simulated samples for crises that last between 6 and 16 quarters. The grey area shows where 80% of the simulated paths are situated, all of which have been normalized by their period 0 value.

On average, output falls 10% below its pre-crisis level in the model, consumption drops more than output and investment contracts by more than one fourth a few periods after the transition. The average response of the trade balance shows every characteristic of a sudden stop, with the trade surplus quickly rising to 7% of GDP on average. One important feature of the responses is the persistence of

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[18]See Appendix 2.7.4 for more details.
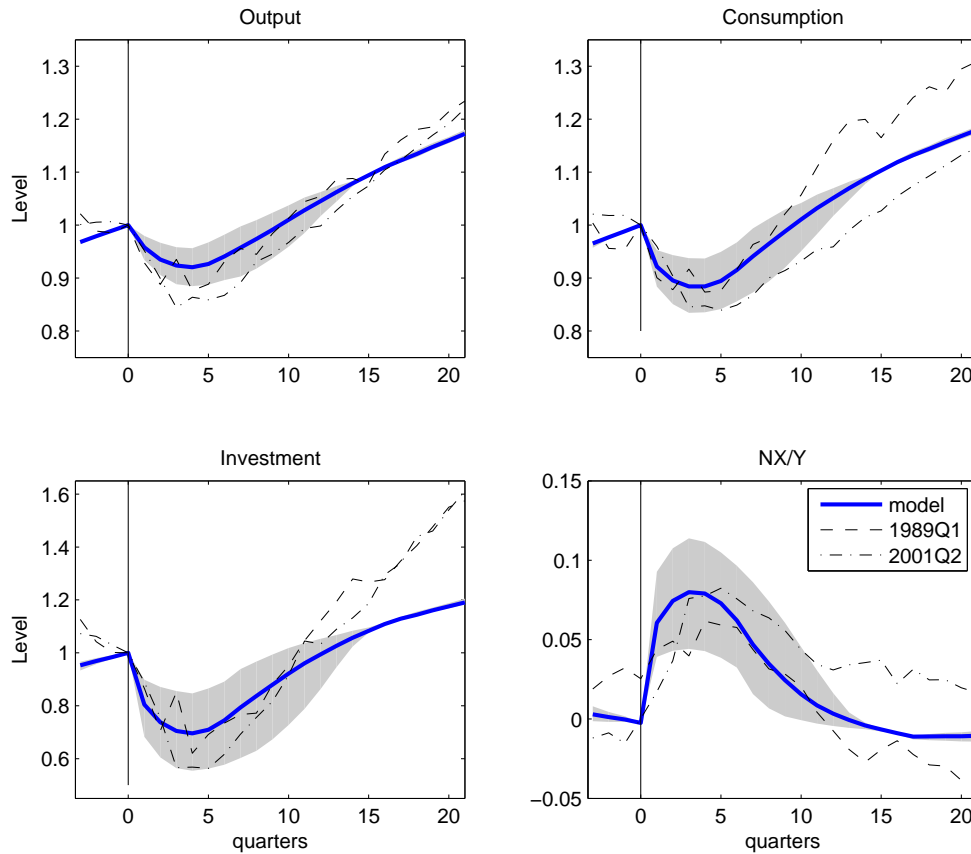
FIGURE 2.6: Response to a Crisis.

Variables are in levels. For output, consumption and investment the period 0 value is normalized to one. The grey area indicates the region in which 80% of the simulated sample moments lie. Broken lines are Argentinean data with period 0 equal to 1989Q1 and 2001Q2 respectively. See Appendix 2.7.4 for more details.

the crisis induced dynamics: it takes very long for output, consumption and investment to return to their trend values. We believe this result can be reconciled with the findings of Aguiar and Gopinath (2007) who, in the context of a standard frictionless model, assign a predominant role to permanent shocks to account for fluctuations in emerging economies. Using a longer sample for Argentina and Mexico, however, García-Cicco *et al.* (2010) argue that there is not much support in data for the predominance of permanent shocks. In our model technology shocks are stationary, but the specification of the financial friction and the regime switching nature of the financial shock imply on average persistent deviations in measured TFP. The average response of the trade balance is much less persistent, which is in line with the arguments made by García-Cicco *et al.* (2010). Judging by Argentina's experience in the 1989 and 2001 crises, the model produces crisis dynamics that are overall empirically plausible. One potential discrepancy is the speed of the recovery of investment: in both instances it has posted a higher

growth rate onwards from 2 or 3 years after the start of the crisis than the rate predicted on average by the model. This could be a failure of the model, but it could also be due to positive realizations of shocks.
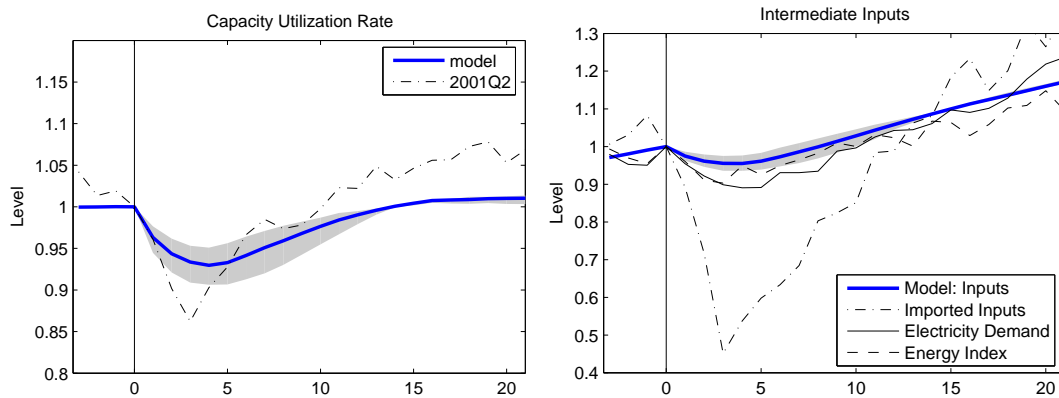
FIGURE 2.7: Response to a Crisis of Utilization Rate and Intermediate Inputs.
Left Panel: The solid line is the response of capacity utilization rate in the model. The broken line corresponds to Argentinean data on industrial capacity utilization rate with period 0 equal to 2001Q2. *Right Panel:* The solid line is the response of intermediate inputs in the model. The other series correspond to Argentinean data on imported intermediate inputs, on electricity demand and on the synthetic energy index, with period 0 equal to 2001Q2. For all series in both panels the period 0 value is normalized to one. See Appendix 2.7.4 for more details.

In Sections 2.5.2 and 2.5.3 we repeat this exercise for alternative specifications of the model and show that both intermediate inputs and variable capacity utilization matter for the quantitative success of the model in terms of crisis dynamics. Here we provide evidence that these modeling assumptions are, overall, empirically plausible by comparing the model response to a crisis of the utilization rate and intermediate inputs with some data counterparts.[19] Figure 2.7 shows that capacity utilization decreased substantially during the 2001 crisis, and Figure 2.2 suggests this was also the case in the 1989 crisis. The model captures this fact; if anything, it somewhat understates the decrease in utilization in the data. Although there is no aggregate series on the use of intermediate inputs in Argentina, there are three series that we can use as indirect evidence for samples that include the 2001 crisis: (1) imports of intermediate inputs (which account for around 40% of total imports); (2) demand of electricity; and (3) a synthetic energy production index. Figure 2.7 compares the average evolution of intermediate inputs in the model

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[19]The details of the data used are reported in the Appendix 2.7.1. The limited sample for the series on capacity utilization and intermediate inputs precludes us from including them among the series for which we compare second moments from simulations.

during crises and the path of those three series around the 2001 crisis. All variables show a significant decrease. The magnitude of the average drop of material inputs in the model is consistent with the paths of the energy index and electricity demand in data. The fall in imported intermediate inputs during the 2001 crisis is larger than what the model predicts. However, in reality the imported inputs are only a fraction of the total. It is likely that during crises firms substitute imported inputs for domestic inputs, such that the actual decrease is smaller. Also, the data is on flows of imports and does not consider changes in inventories that might have taken place at the onset of the crisis.

The role played by the credit friction in producing the abrupt drop in output during crises depends on the assumed elasticity of substitution between material inputs and value added. Unfortunately, there is no data from Argentina to estimate this elasticity. Equation (2.17) implies that the output response to a shift to the crisis regime is determined by the induced change in measured TFP. We can assess the sensitivity of our results to different elasticities by looking at how measured TFP responds for alternative values of the elasticity $1/(1-\rho)$. Figure 2.8 plots the average response of $\mathcal{A}_t(A_t, q_t)$ to a crisis under different elasticity values: 0.0001 (our benchmark calibration value), 1, and 100 (infinite elasticity). According to Bruno (1984) and Basu (1996), a unitary elasticity is most likely an upper bound for the US. Fortunately, the difference in the reaction of measured TFP between a very low elasticity and a unitary elasticity is very small. With infinite elasticity of substitution the drop in measured TFP is obviously much smaller, and in that case the model would fail to match the drop in output in the data. However, a low elasticity seems more realistic.

Dynamics in Response to the Actual Interest Rate Series   Figure 2.9 plots detrended output, consumption, investment and the trade balance to GDP ratio predicted by the model when we embed the observed series for the interest rate in Argentina depicted in Figure 2.1. For this exercise we keep the level of technology equal to its long run average. The figure also depicts the corresponding variables for Argentinean data. The model series generated only by interest rate movements track the observed series remarkably well. The fit for the trade balance to GDP ratio is particulary good. The main discrepancy is that the model overstates the downward reaction of investment in the 2001 crisis. Again, it might be that the simple structure of the model misses some dimensions of the adjustment in the
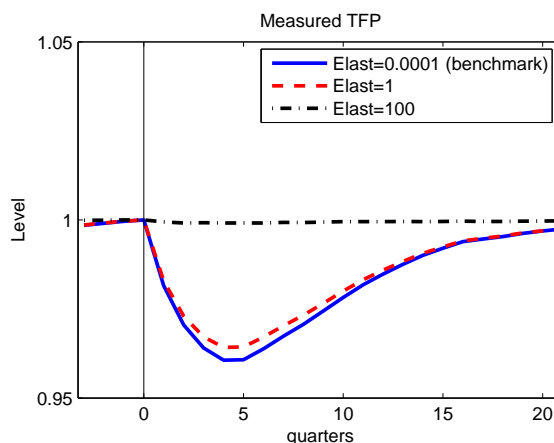
FIGURE 2.8: Response to a Crisis of measured TFP in the benchmark model, equation (2.18), for different values for the production elasticity of substitution $1/(1-\rho)$.

data, or it might be simply due to positive realizations of shocks in data after the crisis (e.g. the boom in commodity prices).
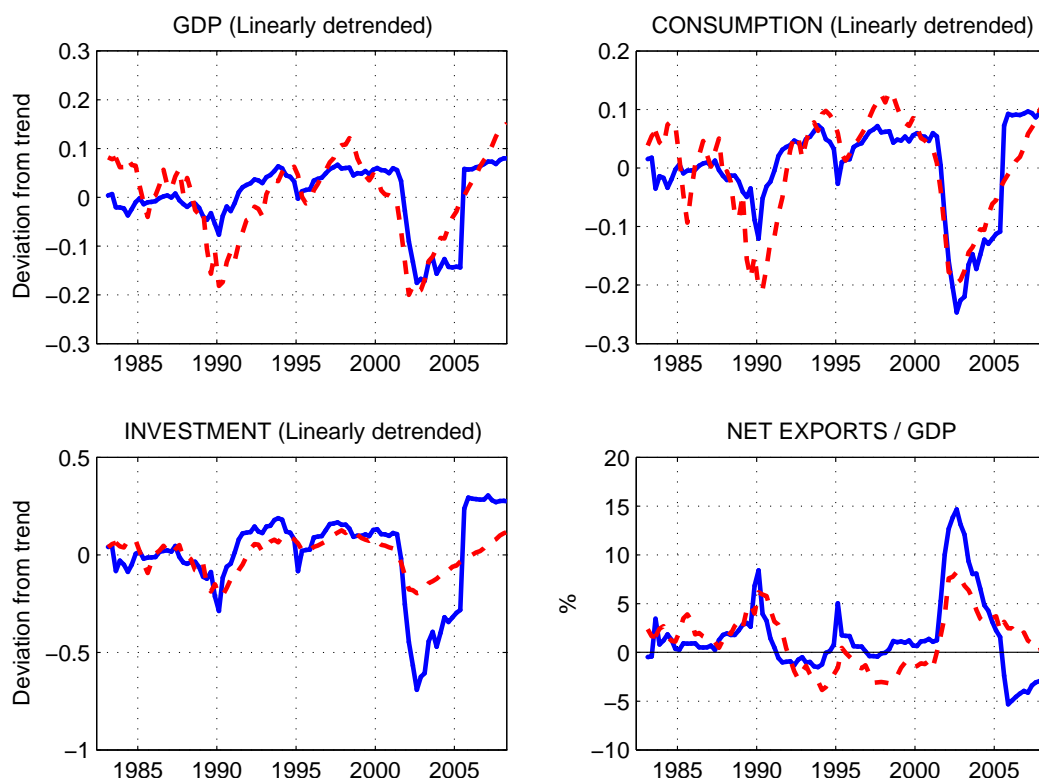
FIGURE 2.9: Model Predictions to Actual Real Interest Rate Series. Simulated (solid lines) and actual (broken lines) macroeconomic aggregates when the actual series for the real interest rete is fed into the benchmark model. Output, consumption and investment variables are linearly detrended.

Higher Order Properties. The nonlinear nature of interest rates is reflected in the unconditional probability distributions of the variables. Model evaluation in terms of higher order properties complements the evidence on plausible dynamics during crises: if the model response to a crisis were in line with data but crises were too frequent or too rare, the model would fail in terms of its predicted unconditional probability distributions. Figure 2.10 reports fitted densities for both model and Argentinean data series. The distributions of output, consumption and investment in data show a clear tail to the left, reflecting the large declines that follow current account reversals. The latter are reflected in the right tail for the trade balance. Figure 2.10 shows that the model variables display the same pattern of asymmetry. The sample skewness of data and model series is reported in Table 2.4: Although there are some differences in values, the direction of the asymmetry is always correct. Another check of model performance is a comparison of outcomes in crises and booms. We compute the average of each detrended series in the lower tail of the distribution (5% quantile) and their average in the upper (95% quantile) tail of the distribution. We then construct the ratio of the distance to trend of crises outcomes over the distance to trend of booms outcomes. These crisis-to-booms ratios both for data and the model series are reported in Table 2.4. The asymmetry between good and bad times in the model is in line with the data, notwithstanding a significant discrepancy for the investment series. The relative success in fitting the higher order moments of the macro variables is in the first place due to the asymmetric distribution of interest rates. However, how these translate quantitatively into asymmetries in the distribution of output and other variables depends on sufficiently strong propagation caused by model features such as credit frictions and variable capacity utilization.

Overall, the evidence provided in this section shows that the model succeeds in producing plausible sudden stop dynamics and in generating asymmetries in the probability distributions of macro variables that are similar to Argentinean data.

2.4.3 The Relative Importance of Shocks and the Role of Crises

We now turn to the quantitative importance of interest rate shocks and crises for understanding the properties of the Argentinean business cycle. The last two
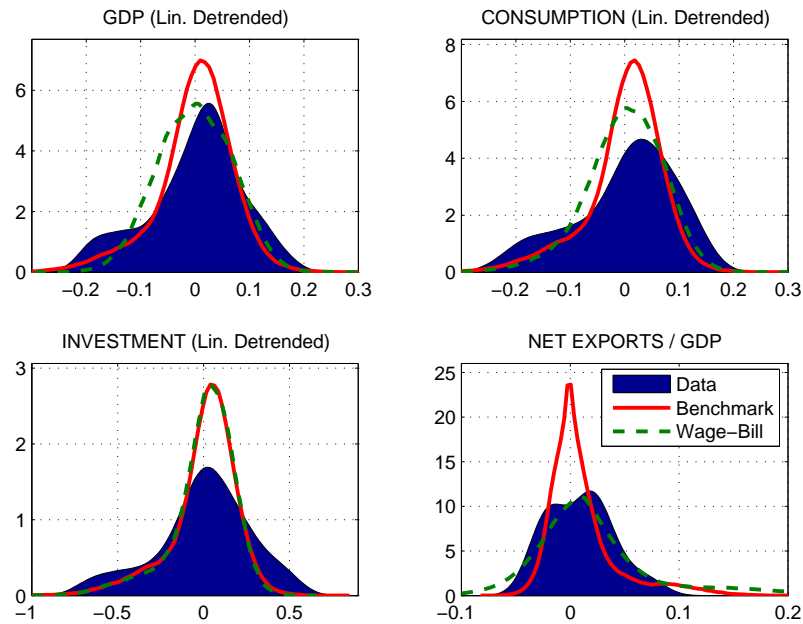
FIGURE 2.10: Probability Distribution of Data and Model Macro-Aggregates. Fitted kernel densities to data (areas), benchmark model (solid lines) and wage-bill model macroeconomic aggregates (broken lines). Output, consumption and investment correspond to linear detrended series.

TABLE 2.4: Asymmetry in Macro-Aggregates: Data, Benchmark and Wage-Bill Model.

	Skewness			Crises-to-Booms ratio		
	Data	Benchmark	Wage-Bill	Data	Benchmark	Wage-Bill
Output	−0.5	−0.62	−0.03	1.3	1.4	1.0
Consumption	−0.68	−0.92	−0.42	1.5	1.6	1.2
Investment	−0.53	−1.02	−1.03	1.3	1.7	1.4
Trade Balance to GDP	+0.37	+1.56	+1.13	0.7	0.4	0.5

Output, consumption and investment series for Argentina have been linearly detrended. The crises-to-booms ratio for each macro-aggregate is computed as the distance from outcomes during crises to trend over the distance from outcomes during booms to trend. Outcomes during crises (booms) for each variable correspond to the average of the realizations smaller (bigger) than the 5% (95%) quantile of the distribution.

columns in Table 2.3 contain the results of two simulation experiments aimed at quantifying the role of interest rate shocks. In the first experiment, we isolate the role of crises by computing the moments for 1000 samples in which the crisis regime does not occur. When simulating the data, we use the same policy functions as before but force the realized interest rate process to be generated by an AR(1) process, the parameters of which are those of the estimated tranquil

regime. In the second experiment, we compute the moments when interest rate shocks are absent and there are only technology shocks. In both experiments, we do not change any of the parameter values of the model.

The first observation is that the presence of crises is the main reason why interest rate shocks are important in accounting for business cycle volatility in Argentina. The standard deviation of output growth is 6.5% in the data. Without crises occurring, the standard deviation drops to 3.2%, or 51% lower than the value in the data. Removing the interest rate shocks altogether further reduces the standard deviation, but only by 0.4% or another 6%. Therefore, it is almost exclusively the crisis episodes that comprise the contribution of interest rate shocks to business cycle volatility.

The second main result from our experiments is that the ability of the model to match the data along several important dimensions also depends to a large extent on the presence of crises. Without crises, the relative volatility of consumption drops from 1.10 to 0.83, which is much lower than in the data and closer to values from developed small open economies. The correlation of the trade balance with output growth drops from -0.52 to -0.12, such that the trade balance is much less strongly countercyclical. When interest rate shocks are removed altogether, the relative volatility of consumption drops further to 0.75, and the trade balance becomes strongly procyclical with a correlation of 0.70. These findings are of course reminiscent of Neumeyer and Perri (2005), García-Cicco *et al.* (2010) and others, who show that the standard RBC model with only technology shocks fails along these important dimensions. Our results suggest that while we need to incorporate financial frictions to bring the model closer to the data, quantitatively it is the combination with the occurrence of crises that matters most for the improved performance.

These results contrast with those of Mendoza (2010), who finds in model simulations based on a calibration to Mexican data that the occurrence of crises does not influence the properties of regular business cycle fluctuations very much. The key difference with our analysis is that the model in Mendoza (2010) has the appealing property that sudden stop events are triggered endogenously. Crises dynamics are explained by a suddenly binding collateral constraint producing debt deflation dynamics. We believe the main reason for the discrepancy is that self

insurance tends to make severe crises more unlikely in models of optimizing agents with rational expectations. In Mendoza (2010), only when a particular history of favorable shocks leading to increased borrowing is followed by a sudden reversal of fortune including an adverse interest rate shock as well as a negative technology shock, does the model produces dynamics that are quantitatively as observed during emerging market crises. In our approach, sudden stops are exogenously generated by regime shifts at a frequency that is determined by the empirical estimates of the regime switching model of interest rates. If we define a sudden stop as Mendoza (2010) as a situation in which the economy is in the crisis regime and the trade balance to GDP ratio is at least one standard deviation above the sample mean, the ergodic probability of sudden stops in the model is 12%.[20] In the Argentinean sample this probability is about 9%. An advantage of our approach is that it generates empirically more plausible probabilities of tail events, which is one of the reasons we emphasize model evaluation on the basis of the higher order properties of the macroeconomic variables.

2.5   Exploring Alternative Modeling Assumptions

In this section we present some alternative models in order to gain further insight into the quantitative contribution of the main features of our benchmark model. In the first exercise, we allow for the domestic credit friction to be regime dependent. A second experiment evaluates the role of variable rate of capacity utilization. Finally, we compare our model with a basic small open economy model with a financial friction linked to the wage bill instead of intermediate inputs. This last exercise employs a framework that is very similar to Neumeyer and Perri (2005) or Uribe and Yue (2006) but with nonlinear shocks to the interest rate.

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[20]Mendoza (2010) defines sudden stop states as those in which the collateral constraint binds and the trade balance to GDP ratio is at least one standard deviation above the mean. The frequency of sudden stops in his calibrated model is 3.3%.

2.5.1   A Model with Regime Dependent Financial Frictions

Before, we demonstrated that it is the combination of financial frictions and crises that accounts for virtually all of the contribution of interest shocks to business cycle volatility. This suggests that what matters most quantitatively is the tightness of the financing constraint around crisis episodes, but not necessarily during tranquil times. To capture this idea, we modify the model by allowing the parameter φ to take on different values across the different regimes. Our motivation is twofold. First, although there are no direct aggregate empirical measures of φ or the value of working capital, a criticism of models with working capital frictions has been that, to be successful, an implausible large stock of working capital or collateral needs to be assumed. However, the model in this section implies a much smaller average value for the working capital parameter while leaving the results unchanged or even improved. Second, there is wide consensus that during times of financial stress, access to interfirm credit or trade finance is reduced and firms are forced to adopt cash-in-advance or bank-intermediated financial arrangements. This has important consequences on trade of intermediate inputs and production.[21]

We capture the time varying nature of credit frictions by assuming $\varphi = 0$ in the tranquil regime and $\varphi = 0.80$ during the crisis regime.[22] Given our estimated regime switching process for Argentina, where the ergodic probability of the tranquil regime is 77%, the average value of φ is around 0.22, almost 80% lower than the value under the benchmark model. This implies that the average stock of working capital is 6.3% of GDP in this model, while this ratio is 27% in the benchmark model. In order to be consistent with the same target statistics as the benchmark calibration, only very minor changes in the other parameter values were required (see the footnote in Table 2.5).

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[21]See Auboin and Meier-Ewert (2003), International Chamber of Commerce (2008) and International Monetary Fund (2003).

[22]We assume $\varphi = 0.8$ in the crisis regime since we found that, when setting $\varphi = 1$, the combined effect of movements in φ and the interest rate shocks yielded excessive output volatility: the standard deviation of output growth in the simulations exceeded the value in the data, even when setting the standard deviation of the technology shock to zero. To make the results more comparable, we therefore chose to keep the volatility of technology shocks the same as in the benchmark calibration, and instead adjust the value of φ to match the observed standard deviation of output growth.
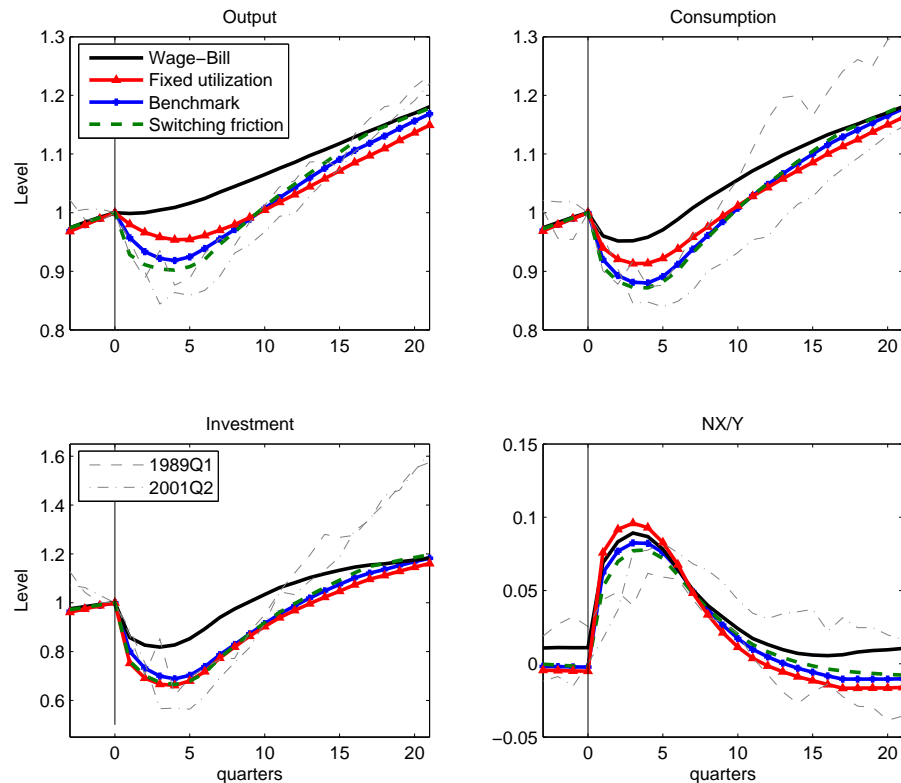
FIGURE 2.11: Response to a Crisis: Comparison of Alternative Models. Switching friction denotes the model with regime dependent financial frictions in Section 2.5.1; Fixed utilization refers to the model in Section 2.5.2; and Wage-Bill corresponds to the model in Section 2.5.3. Thin broken lines are Argentinean data with period 0 equal to 1989Q1 and 2001Q2 respectively. See Appendix 2.7.4 for more details.

The third column in Table 2.5 displays the relevant business cycle moments of the model with a regime dependent financing friction. The results are remarkably similar to the benchmark model and, in some aspects, even more in line with the Argentinean data. The relative standard deviation of consumption is almost identical to the benchmark model value. The trade balance remains strongly countercyclical, but the value of -0.45 is closer to the observed value of -0.30, which is now also within 10%-90% quantiles of the simulated moments. Since now interest rate shocks directly affect labor and capital productivity only in the crisis state, the cross correlations of output, consumption and investment with the interest rate are considerably lower. This brings these numbers closer to the values in the data, which, except for investment, are now within the 10%-90% quantiles of the simulated moments. Removing the crises lowers the volatility of output by 59%, as opposed to 51% in the benchmark. Removing all interest rate shocks (as well as keeping $\varphi = 0$) does not further reduce output volatility significantly. This

confirms the result of the benchmark model that it is crises episodes that are key for the empirical success of the model. Outside of crises episodes, the financing friction is by and large inconsequential as movements in interest rates are far too small. Figure 2.11 compares the paths of the main macro-aggregates during sudden stops in the modified model. Because of the simultaneous tightening of credit conditions, the average drops in output, consumption and investment are more pronounced than in the benchmark model.

All of this suggests, first, that a lack of evidence of sizeable financial constraints in a sample dominated by tranquil episodes does not automatically imply that these frictions are irrelevant for understanding emerging market fluctuations. This has important implications in terms of validating models with working capital frictions empirically. It also suggests that the assumption of tightening domestic credit conditions occurring in conjunction with rises in interest rates and interest rate volatility is empirically plausible. This extension is particularly appealing in the light of evidence that trade credit is an important channel through which financial shocks affected real outcomes during recent financial turmoils.

2.5.2 A Model with Fixed Capacity Utilization

Before, we pointed to the role of variable capital utilization as an amplification mechanism of interest rate shocks in the benchmark model, and we showed that the model predictions for the utilization rate during crises is not contradicted by available data. To further assess the relative contribution of this feature, in this section we solve a different version of the model in which utilization is kept constant. The parameters are recalibrated to remain consistent with the moments of the ergodic distribution. The fourth column of Table 2.5 presents business cycle moments for this alternative model. In terms of second moments, the model still performs relatively well. Smaller amplification of interest rate shocks means technology shocks must account for a larger share of output volatility than in the benchmark model. As a result, the model with fixed utilization yields lower consumption volatility: the relative standard deviation of consumption is now 1.03, but the moment in data still lies within the 10%-90% quantiles of simulated moments. The smaller propagation of interest rate shocks weakens the countercyclical nature of interest rates and lowers the negative correlation of the trade balance with output relative to the benchmark model: both moments in the data now lie

within the 10%-90% quantiles of the simulated moments. Overall, the correlations of consumption, investment and the trade balance with output growth, as well as the correlations of all variables with interest rates are consistent with the data.

However, Figure 2.11 shows that the specification with fixed capacity utilization is unable to explain the magnitude of the response of output and consumption to crises and consequently fails to match the higher order properties of the data (e.g. the skewness of output and consumption is -0.13 and -0.29 respectively, while it was -0.62 and -0.92 in the benchmark model). This finding is consistent with the arguments in Meza and Quintin (2007). The main discrepancy with the Argentinean crises is in the size of the drop in economic activity and in the speed of the adjustment. When a rise in the interest rate reduces measured TFP, this affects directly the marginal productivity of capital. In the benchmark model, variable capacity utilization allows households to adjust the amount of capital services supplied, leading to an immediate reduction in output. The volatility of output growth is reduced by 18% when we remove the crises, as opposed to 51% in the benchmark model. Eliminating interest rate shocks altogether, the additional drop in output volatility is quantitatively very small. Therefore, the volatility contribution of interest rate shocks depends on the feature of varying capacity utilization, but it is still almost exclusively the presence of crises that comprises the effect of interest rate fluctuations.

2.5.3 A Model With a Working Capital Constraint Linked to the Wage Bill

In this section we wish to clarify further the quantitative contribution of linking the working capital friction to intermediate inputs rather than the wage bill, and its interaction with the nonlinearity of interest rates. The model we use for comparison has fixed utilization, only capital and labor are used in production and the working capital friction is linked to the wage bill (the details are given in Appendix 2.7.5). The model is thus very similar to Neumeyer and Perri (2005) or in Uribe and Yue (2006). The key difference is that we embed into the model the same nonlinear process for the interest rate as in our benchmark model and employ a nonlinear global solution method. Business cycle moments for the wage bill model are reported in the fifth column of Table 2.5. Overall it is relatively consistent with

TABLE 2.5: Simulation Results for Alternative Models (Year on Year Growth Rates)

		Data	Benchmark	Switching φ_t	Fixed u_t	Wage-Bill
a) Standard Deviations						
Consumption	$std(g_c)/std(g_y)$	1.14	1.10	1.09	1.03	1.04
			(0.94,1.25)	*(0.96,1.23)*	*(0.90,1.19)*	*(0.88,1.21)*
Trade balance to GDP	$std(nx/y)$	0.029	0.032	0.032	0.039	0.036
			(0.021,0.042)	*(0.021,0.043)*	*(0.026,0.055)*	*(0.021,0.049)*
b) Cross-Correlations with g_y						
Consumption	$corr(g_c,g_y)$	0.94	0.95	0.95	0.92	0.88
			(0.92,0.97)	*(0.92,0.97)*	*(0.88,0.96)*	*(0.81,0.94)*
Investment	$corr(g_x,g_y)$	0.92	0.94	0.93	0.69*	0.69*
			(0.91,0.96)	*(0.90,0.96)*	*(0.57,0.79)*	*(0.57,0.82)*
Trade balance to GDP	$corr(nx/y,g_y)$	−0.30	−0.52*	−0.45	−0.31	−0.03*
			(−0.66,−0.36)	*(−0.62,−0.23)*	*(−0.54,−0.07)*	*(−0.25,−0.19)*
c) Cross-Correlations with R						
Output	$corr(g_y,R)$	−0.21	−0.45*	−0.35	−0.38	−0.13
			(−0.59,−0.31)	*(−0.50,−0.17)*	*(−0.56,−0.20)*	*(−0.32,0.07)*
Consumption	$corr(g_c,R)$	−0.26	−0.40	−0.35	−0.37	−0.24
			(−0.56,−0.25)	*(−0.50,−0.21)*	*(−0.54,−0.20)*	*(−0.42,−0.07)*
Investment	$corr(g_x,R)$	−0.07	−0.32*	−0.26*	−0.30*	−0.23*
			(−0.47,−0.17)	*(−0.41,−0.12)*	*(−0.46,−0.15)*	*(−0.39,−0.06)*
Trade balance to GDP	$corr(nx/y,R)$	0.71	0.68	0.73	0.61	0.86*
			(0.37,0.88)	*(0.43,0.92)*	*(0.29,0.85)*	*(0.81,0.91)*

Numbers in parenthesis are 10% and 90% quantiles. An asterisk denotes that the corresponding data moment does not lie within these quantiles. For the model with fixed utilization, the only parameters that are different from the benchmark calibration in Table 2.2 are $\eta = 0.074$, $\sigma_A = 0.00915$, $\phi_k/2 = 9.05$ and $\beta = 0.96235$. For the model with a regime dependent financial friction, the only parameter that is different from the benchmark is $\beta = 0.95984$. For the wage-bill model the parameters are presented in appendix.

the data in terms of the second order properties of simulated series. One short-coming of the wage bill model is that the trade balance to GDP ratio becomes acyclical: the average correlation with output growth is only -0.03, while in the data is -0.30 which is outside the 10% and 90% quantiles of the simulated sample moments. The absence of a countercyclical trade balance is very similar to the simulation results in Neumeyer and Perri (2005) for the model with independent interest rate and technology processes.

More relevant implications of linking the friction to material inputs and its interaction with nonlinear interest rates become clear when we analyze higher order moments and dynamics around crises episodes. Figure 2.10 compares the probability distribution of endogenous variables from the wage bill and the benchmark model and Table 2.4 reports sample skewness and the crises-to-booms statistic. The degree of asymmetry of consumption, investment and the trade balance to GDP ratio in both the benchmark and the wage bill model is very much in line with data. As argued before, this success is due to the regime switching nature of the interest rate we estimate from data. However, the distribution of output implied by the wage bill model is almost symmetric: the skewness of detrended GDP is only -0.03 while in data it is -0.50. This lack of asymmetry suggests an important failure in the propagation mechanism of financial shocks to output when the friction is linked to the wage bill. This specification implies that an interest rate shock affects directly only the marginal productivity of labor (see equation (2.41) in the Appendix 2.7.5), while when the friction is linked to material inputs the shock affects directly the marginal productivity of both labor and capital. The comparison between the wage bill model and the fixed utilization model shown in the upper left panel of Figure 2.11 is particularly illustrative: Although the only specification difference is linking the friction to the wage bill rather than to intermediate inputs, the response of output to a crisis in the wage bill model is much milder and further away from the reaction in data. These results are consistent with the fact that our benchmark model assigns a larger role for interest rate shocks in accounting for output volatility in Argentina in comparison with Neumeyer and Perri (2005): Our counterfactual experiments suggested a reduction of output volatility of more than half once interest shocks are eliminated, while in their paper the reduction is around 30%.

2.6 Conclusion

The occurrence of dramatic crises in many emerging markets raises the question of their role in determining the distinctive features of emerging market fluctuations such as the high volatility of consumption and the strong countercyclicality of the trade balance. Our analysis suggests that these may be driven to a large extent by the nonlinear behavior of interest rates that is typical of emerging markets. Interest rates are well characterized by a regime switching process alternating between a low level/low volatility regime and an infrequent high level/high volatility regime. We embed a nonlinear process estimated for Argentina into a neoclassical small open economy model with financial frictions and variable capacity utilization. The nonlinearities turn out to be important for the quantitative properties of small open economy models in terms of determining precautionary savings and consumption smoothing behavior. Our model performs well not only in terms of matching the traditional second moments of the data but also in terms of fitting the higher order moments of the main macroeconomic aggregates and in producing plausible endogenous dynamics during crises episodes. We emphasize the empirical evaluation of the model in terms of higher order moments of endogenous variables and their dynamics during crises episodes. Our sensitivity exercises indicate that these can be very informative for discriminating between business cycle models for emerging markets. For instance, the inclusion of variable capacity utilization and linking credit frictions to the purchase of intermediate inputs prove important in generating empirically plausible asymmetries in the probability distributions of key macroeconomic variables.

Our counterfactual experiments indicate that interest rate fluctuations associated with financial crises can explain a large part of the output volatility observed in Argentina. We also argue that financial frictions are essential for explaining emerging market fluctuations, but almost exclusively because of their effects in crisis episodes. This outcome supports the modeling approach of Mendoza (2010), who shares with us the emphasis on nesting infrequent dramatic crises with regular fluctuations and views crises as times when financing constraints become particularly stringent.

An important challenge for future research employing dynamic models with rational forward looking agents is to reconcile the occurrence of severe crises with

the incentive for households to engage in precautionary savings behavior in anticipation of the possibility of future crises. Modeling crises as rare exogenous shifts to a regime of high and volatile interest rates greatly reduces the agents' ability and incentives to self insure relative to models where crises arise endogenously, such as in Mendoza (2010). This difference in modeling approach has important consequences for the incidence of crises and consequently for their impact on the properties of business cycles in emerging economies. We acknowledge nevertheless that the small open economy assumption for interest rates neglects an endogenous default risk component that affects the country spread, which is a shortcoming of the modeling approach. However, what this spread captures is rather the foreign investors' perceived probability of default, which might not be necessarily driven by changes in domestic fundamentals. In that sense, the regime switching nature of interest rates we find in data might respond to abrupt shifts in investors' expectations about, for instance, the willingness of other investors to rollover maturing debt, or about the future path of domestic policy in light of developments in other economies. To the extent that these phenomena play an important role in the pricing of emerging markets' debt as many empirical studies suggest, viewing financial crises as being triggered by exogenous switches in regime seems a reasonable first approximation.

Although we targeted the calibration and empirical evaluation of the model to Argentina, we believe the main results in this chapter extend broadly to other emerging economies. The regime switching estimation shown in Chapter 1 for a sample of emerging markets revealed that the asymmetric distribution of interest rates is similar in other countries. Moreover, the skewed distributions of some macroeconomic aggregates, reflecting the occasional occurrence of severe crises, is a common feature for these economies. It is these asymmetries, rather than just higher volatility, that seem to constitute a key difference with most developed small open economies.

2.7 Appendix Chapter 2

2.7.1 Data Sources and Transformations

We use data for Argentina from 1980Q1 to 2008Q2 for GDP, consumption, investment, exports and imports, and from 1983Q1 to 2008Q4 for the real interest rate. The data used are plotted in Figures 2.1 and 2.2. The series from the National Accounts are in constant prices (millions of pesos, prices of 1993). GDP is obtained from the Instituto Nacional de Estadisticas y Censos (INDEC) for the whole period. Consumption corresponds to private plus public consumption. Series on consumption, investment, imports and exports are obtained from INDEC for the period 1993Q1 to 2008Q2 and extended backwards until 1980Q1 by splicing with the data in Neumeyer and Perri (2005). To compute the average quarterly growth rate of GDP we excluded the rates corresponding to quarters 1989Q2 to 1990Q2 and 2001Q3 to 2004Q1, corresponding to crises periods. The beginning of the crises were dated using the estimated crisis probabilities from the regime switching model. The end of each crisis was dated at the period at which output reached its pre-crisis level.

The data on capacity utilization rate, imported intermediate inputs, energy index, electricity demand, employment and total loans to the private sector shown in Figure 2.2 was obtained from CEIC database (http://www.ceicdata.com/). The utilization rate corresponds to the quarterly average of the industrial capacity utilization rate series constructed by the Fundación de Investigaciones Económicas Latinoamericanas (FIEL) since 1990M01. The electricity demand series is in physical units (GWh), available since 1999M01, and is constructed by the Wholesale Electricity Market Regulatory Company; we report the quarterly average. The synthetic energy index (2003=100) is reported by the INDEC from 1993M01 onwards. The imported intermediate inputs series is constructed by the INDEC, corresponds to millions of US dollars and is available since 1992M01. We take the quarterly average and convert it to millions of pesos, prices of 1993, using the GDP implicit price deflator for imports (INDEC, available from 1993Q1). The total loans to the private sector series (1993Q1-2008Q4) corresponds to the sum of loans to the non-financial private sector in foreign and in domestic currency, constructed by the Central Bank, expressed both in real pesos (millions of pesos,

1993 prices). The employment series correspond to the quarterly average of employed workers (thousands of people) reported by the INDEC as registered in the social security system (SIJP), available since 1995M01.

The real interest rate is constructed as in Neumeyer and Perri (2005). The nominal interest rate in US dollars correspond, each quarter, to the average daily yield for the 90-day U.S. T-bill in the secondary market plus the average J.P. Morgan EMBI+ Stripped Spread. The real rate is obtained by deflating the nominal rate by the U.S. GDP Deflator expected inflation. Quarterly expected inflation is computed as the average of the actual GDP Deflator inflation in that quarter and in the three preceding ones. From December 1993 onwards we use the country spread calculated by J.P. Morgan. We extend the series backwards at quarterly frequency until 1983Q1 by splicing with the data in Neumeyer and Perri (2005). For the last observation in our sample, 2008Q4, we used preliminary values. For the country spread we used values available until November 11th, 2008, while for the U.S. T-bill yield we used values until November 13th, 2008. Regarding the U.S. GDP deflator inflation, we fitted an AR(1) model to its growth rate with data from 1980Q1 to 2008Q3 and projected the value for the last quarter: 2008Q4.

2.7.2 Measured TFP

Substituting m_t from equation (2.16) in equation (2.10) and rearranging we can obtain:

$$\left(\frac{z_t}{f_t}\right)^{1-\rho} = \left[1 - \mu A_t^{\frac{\rho}{1-\rho}} (1 + \varphi q_t)^{-\frac{\rho}{1-\rho}}\right]^{-\frac{1-\rho}{\rho}} A_t^{1-\rho} (1-\mu)^{\frac{(1-\rho)^2}{\rho}} \tag{2.22}$$

Then, (2.22) is plugged in equations (2.14) and (2.15), giving:

$$r_t^k = \alpha \left(\frac{A_t^{\frac{\rho}{\rho-1}} - \mu (1 + \varphi q_t)^{\frac{\rho}{\rho-1}}}{1-\mu}\right)^{\frac{\rho-1}{\rho}} \frac{f_t}{k_t^s} \tag{2.23}$$

$$w_t = (1-\alpha) \left(\frac{A_t^{\frac{\rho}{\rho-1}} - \mu (1 + \varphi q_t)^{\frac{\rho}{\rho-1}}}{1-\mu}\right)^{\frac{\rho-1}{\rho}} \frac{f_t}{h_t} \tag{2.24}$$

Finally, the resulting expressions for r_t^k and w_t are used in the definition of GDP, $y_t = r_t^k u_t k_t + w_t h_t$, to obtain:

$$y_t = \mathcal{A}_t(A_t, q_t)(u_t k_t)^\alpha (\Gamma_t h_t)^{1-\alpha} \tag{2.25}$$

$$\mathcal{A}_t(A_t, q_t) = \nu \left(\frac{A_t^{\frac{\rho}{\rho-1}} - \mu(1 + \varphi q_t)^{\frac{\rho}{\rho-1}}}{1 - \mu} \right)^{\frac{\rho-1}{\rho}} \tag{2.26}$$

2.7.3 Numerical Algorithm

The algorithm seeks an approximate solution to the following system of stochastic difference equations

$$\hat{y}_t = \hat{c}_t + \hat{x}_t + \frac{\hat{d}_t}{g} - R_t^{-1}\hat{d}_{t+1} \tag{2.27}$$

$$\widetilde{\lambda}_t = \left(\hat{c}_t - \zeta \frac{h_t^{1+\psi}}{1+\psi} \right)^{-\gamma} \tag{2.28}$$

$$\zeta h_t^\psi = (1-\alpha)\frac{\hat{y}_t}{h_t} \tag{2.29}$$

$$\eta u_t^\omega = \alpha \frac{g\hat{y}_t}{u_t \hat{k}_t} \tag{2.30}$$

$$\widetilde{\lambda}_t = \frac{\beta}{g} \mathrm{E}_t \left[\widetilde{\lambda}_{t+1} \right] R_t \tag{2.31}$$

$$\widetilde{\lambda}_t \left(1 + \frac{\phi_k}{g} \left(\frac{\hat{k}_{t+1}}{\hat{k}_t} - 1 \right) \right) = \frac{\beta}{g} \mathrm{E}_t \left[\widetilde{\lambda}_{t+1} \left(\alpha \frac{g\hat{y}_{t+1}}{\hat{k}_{t+1}} + 1 - \delta - \eta \frac{u_{t+1}^{1+\omega}}{1+\omega} + \frac{\phi_k}{2} \left(\left(\frac{\hat{k}_{t+2}}{\hat{k}_{t+1}} \right)^2 - 1 \right) \right) \right] \tag{2.32}$$

where $\hat{y}_t$ is given in (2.17). Denoting the vector of state variables by $S_t = \left[\hat{k}_t, \hat{d}_t, R_t, s_t, A_t \right]$, we approximate the policy functions for the state variables $\hat{d}_{t+1} = d(S_t)$ and $\hat{k}_{t+1} = k(S_t)$ by piecewise linear functions over a grid, denoted by S, of $21 \times 21 \times 51 \times 2 \times 11 = 494,802$ nodes each and compute the approximate solution by iterating over the policy functions (Coleman (1990)). We combine the procedure with the method of endogenous gridpoints in Carroll (2006) to speed up the algorithm. More specifically, the algorithm is:

Step 1 Obtain an initial guess $k_0(S)$ and $d_0(S)$ from a loglinear approximation around the deterministic steady state.

Step 2 Given the last guess $k_{j-1}(S)$ and $d_{j-1}(S)$, calculate $k'' = k_{j-1}(S)$, $d'' = d_{j-1}(S)$ and find c', y', h', u', λ' using the budget constraint and equations (2.17) and (2.27)-(2.30).

Step 3 Compute

$$e_1 = \frac{\beta}{g} \mathrm{E}\left[\lambda'|R, s, A\right]$$

$$e_2 = \frac{\beta}{g} \mathrm{E}\left[\lambda'\left(\alpha\frac{gy'}{k'} + 1 - \delta - \eta\frac{u'^{1+\omega}}{1+\omega} + \frac{\phi_k}{2}\left(\left(\frac{k''}{k'}\right)^2 - 1\right)\right)|R, s, A\right]$$

and solve for d and k, using

$$e_1 = \lambda R^{-1}$$

$$e_2 = \lambda\left(1 + \frac{\phi_k}{g}\left(\frac{k'}{k} - 1\right)\right)$$

as well as equations (2.17) and (2.27)-(2.30).

Step 4 Using k', d' and k, d, R, s and A, interpolate to obtain $k'' = k_j(S)$ and $d'' = d_j(S)$.

Step 5 Repeat step 2 to 4 until convergence.

2.7.4   Response to a Crisis in Simulations

Model simulated data is obtained by generating 1000 samples of the same size as the actual data, each with a burn-in of 1000 quarters. The model response to a crisis of the different macro aggregates, reported in Figure 2.6, Figure 2.7 and Figure 2.11, is computed in the following way: First, we identify all the subperiods among the simulated series in which the economy was in the crisis regime for at least 6 quarters and not more than 16 quarters. Second, we construct a crisis sample for each of these subperiods including from 5 quarters before to 25 quarters after entering the crisis. We denote the period in which the economy enters the crisis regime as period 1. Third, for each sample we re-scale all the series to the value of the series in period 0 (i.e. the period before entering the crisis regime). Fourth, for each series, we compute the average and the 10% and 90% quantiles across samples.

2.7.5 Model In Section 2.5.3

The models we use in Section 2.5.3 is a version of the model proposed in Neumeyer and Perri (2005) and Uribe and Yue (2006). The main difference with Neumeyer and Perri (2005) is the timing we assume for the opportunity cost of funds for firms. They assume that at the beginning of each period firms issue a within-period bond but at the interest rate of the previous period (even if at the beginning of periods all shocks are known). In our model, as in Uribe and Yue (2006), the opportunity cost of funds for the firm at t is related to the interest rate of that same period. Finally, Uribe and Yue (2006) assume three additional features that we do not include here: they assume that real decisions are made prior to the realization of that period financial shocks, they include habits in consumption and gestation lags in capital accumulation.

The representative household's problem is:

$$\max_{\{c_t, h_t, k_{t+1}, d_{t+1}\}} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(\frac{c_t}{\Gamma_t} - \zeta \frac{h_t^{1+\psi}}{1+\psi} \right)^{1-\gamma} - 1}{1-\gamma} \quad , \tag{2.33}$$

$$\text{s.t.} \quad c_t + x_t + d_t + \Phi\left(d_{t+1}\right) \leq R_t^{-1} d_{t+1} + w_t h_t + r_t^k k_t \quad , \tag{2.34}$$

$$k_{t+1} = x_t + (1-\delta) k_t - \frac{\phi_k}{2} \left(\frac{k_{t+1}}{g k_t} - 1 \right)^2 k_t \tag{2.35}$$

$$\Phi\left(d_{t+1}\right) = \Gamma_t \frac{\phi_d}{2} \left(\frac{d_{t+1}}{\Gamma_t} - \bar{d} \right)^2 \quad , \ \phi_d > 0 \tag{2.36}$$

where all parameters and variables correspond to the benchmark model description in the main text. As in Neumeyer and Perri (2005), a portfolio adjustment cost function was introduced in (2.34) and it was calibrated so that the volatility of the trade balance to GDP ratio remained close to the data counterpart (in the benchmark model $\phi_d = 0$). The parameter $\bar{d}$ is the average debt level from the ergodic distribution.

The only factors of production are capital and labor, and a working capital constraint linked to the wage bill is assumed. The representative firm's problem is:

$$\max_{\{k_t, h_t, \kappa_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left[y_t - w_t h_t - r_t^k k_t - \kappa_t + \kappa_{t-1} \right] , \tag{2.37}$$

$$\text{s.t.} \quad \kappa_t \geq \varphi w_t h_t \tag{2.38}$$

$$y_t = A_t (k_t)^\alpha (\Gamma_t h_t)^{1-\alpha} \tag{2.39}$$

Equilibrium conditions implied by the households' and firms' optimality conditions include:

$$\lambda_t = \frac{1}{\Gamma_t} \left(\frac{c_t}{\Gamma_t} - \zeta \frac{h_t^{1+\psi}}{1+\psi} \right)^{-\gamma} \tag{2.40}$$

$$\Gamma_t \zeta h_t^\psi = \left(1 + \varphi \left(\frac{R_t - 1}{R_t} \right) \right)^{-1} (1-\alpha) \frac{y_t}{h_t} \tag{2.41}$$

$$\lambda_t = \beta E_t \left[\lambda_{t+1} \right] R_t \tag{2.42}$$

$$\lambda_t \left(1 + \frac{\phi_k}{g} \left(\frac{k_{t+1}}{g k_t} - 1 \right) \right) = \beta E_t \left[\lambda_{t+1} \left(\alpha \frac{y_t}{k_t} + 1 - \delta + \frac{\phi_k}{2} \left(\left(\frac{k_{t+2}}{g k_{t+1}} \right)^2 - 1 \right) \right) \right] \tag{2.43}$$

The level of productivity A_t is stochastic and is given by equation (2.21) in the main text. The interest rates are realizations of the Markov switching autoregressive process used for the benchmark model and consistent with estimations for Argentina. The other parameter values are set to remain consistent with the moments of the ergodic distribution and are reported in Table 2.6.

TABLE 2.6: Calibration, Wage-Bill Model in Section 2.5.3.

a) Preferences	Symbol	Value	Target
Discount factor	β/g	0.9608	Trade balance to GDP ratio
Utility curvature	γ	2	Mendoza (1991), ...
Labor disutility weight	ζ	0.62	Normalized labor input
Inverse wage elasticity of labor supply	ψ	0.6	Mendoza (1991), ...

b) Technology			
Capital income share	α	0.38	Labor income share
Growth factor	g	1.0083	Average output growth
Working capital requirement	φ	1	Neumeyer and Perri (2005)
Capital depreciation parameter 1	δ	0.022	I-Y ratio
Capital adjustment cost	$\phi_k/2$	10	Relative investment volatility
Portfolio adjustment cost	$\phi_d/2$	0.09	Trade balance volatility
Saving interest rate ceiling	$\bar{R}$	$1.02^{0.25}$	International riskless rate

c) Technology Shock Process			
Persistence of TFP shock	ρ_A	0.95	Neumeyer and Perri (2005)
Standard deviation of TFP shock	σ_A	0.022	Output volatility

d) Interest Rate Shock Process

See Table 2.1 of the main text.

2.7.6 Other Tables and Figures

TABLE 2.7: Simulation Results in Benchmark Model: Alternative Detrending Methods

		Linear Trend		HP-Filter	
		Data	Model	Data	Model
a) Standard Deviations					
Output	$std(\hat{y})$	0.086	0.068	0.042	0.041
			(0.040,0.100)		*(0.027,0.055)*
Consumption	$std(\hat{c})/std(\hat{y})$	1.07	1.03	1.17	1.11
			(0.87,1.18)		*(0.96,1.26)*
Investment	$std(\hat{x})/std(\hat{y})$	3.15	2.85	3.26	3.08
			(2.44,3.29)		*(2.68,3.50)*
b) Cross-Correlations with $\hat{y}$					
Consumption	$corr(\hat{c},\hat{y})$	0.94	0.95	0.94	0.95
			(0.92,0.97)		*(0.92,0.97)*
Investment	$corr(\hat{x},\hat{y})$	0.96	0.93	0.94	0.95
			(0.90,0.97)		*(0.92,0.97)*
Trade balance to GDP	$corr(nx/y,\hat{y})$	−0.76	−0.50*	−0.67	−0.51
			(-0.73,-0.24)		*(-0.70,0.15)*
c) Cross-Correlations with R					
Output	$corr(\hat{y},R)$	−0.65	−0.79	−0.55	−0.65
			(-0.93,-0.62)		*(-0.80,-0.47)*
Consumption	$corr(\hat{c},R)$	−0.68	−0.84	−0.54	−0.67
			(-0.95,-0.68)		*(-0.84,-0.48)*
Investment	$corr(\hat{x},R)$	−0.63	−0.85*	−0.50	−0.68
			(-0.95,-0.71)		*(-0.84,-0.48)*

For the HP filter, a smoothing parameter of 1600 was used. Numbers in parenthesis are 10% and 90% quantiles. An asterisk denotes that the corresponding data moment does not lie within these quantiles.

Chapter 3

Procyclical Lending Standards and Macroeconomic Fluctuations.

Abstract

This chapter uses a dynamic small open economy model of business cycles with financial frictions to explore how macroeconomic fluctuations are amplified and transmitted across borders when frictions in financial intermediation entail procyclicality in credit conditions. I find that the procyclical behavior of lending standards amplifies shocks to fundamentals beyond the effect attributable to the financial accelerator mechanism. I interpret this extra amplification in the model as resulting from the interaction of financial constraints in the lending and in the borrowing side of financial intermediation. Asset prices play a crucial role in the propagation mechanism as procyclical lending standards reinforce their "overreaction" to shocks signaled by Aiyagari and Gertler (1999). Simulation results suggest the potential for sizeable stabilization gains from "macro-prudential" regulation aimed at containing the procyclical behavior of credit conditions.

3.1   Introduction

The global financial crisis triggered by creditworthiness problems in the U.S. sub-prime mortgage market in mid-2007 has unveiled pervasive interlinkings between the financial system and the real economy, both within and across borders. The large bill due to the crisis in terms of employment, investment and output around the globe has opened the debate on the need to adjust financial regulation, in particular in its macro-prudential dimension. Changes in measured risk, the spread use of mark-to-market valuation in risk management practices and the fast innovation in financial instruments have been signaled as important factors behind the procyclical behavior of lending standards, and in particular for the relaxation of standards and the acceleration of credit growth in the period leading up to the crisis. This chapter uses a dynamic stochastic general equilibrium model (DSGE hereafter) of business cycles with financial frictions to explore how the procyclical behavior of lending standards gets transmitted to asset prices and the real economy, how it affects the propagation of shocks and what are its implications in terms of macroeconomic volatility.

Asset price dynamics are placed at the core of credit cycles and macro-financial linkages. The rise in asset prices in the upturn of cycles (e.g. due an increase in productivity and profits) gets translated into increases in the net worth of borrowers. In the presence of frictions between financial intermediaries and borrowers, this also implies the rise in the value of collateral and the possibility to expand credit, resulting in procyclical lending. The role of borrowers' balance sheets (or their "creditworthiness") in amplifying or generating cycles in macro models has been amply studied in the literature (e.g. Bernanke and Gertler 1989, Kiyotaki and Moore 1997 and Aiyagari and Gertler 1999). However, fluctuations in asset prices also affect the asset side of financial intermediaries' balance sheets, and hence their creditworthiness. Although the financial dynamics of their balance sheet expansions and contractions, the implication in terms of lending standards and the link with the business cycle have been receiving increasing attention in the empirical literature,[1] the role of leverage cycles in macro models has been much less explored. The main contribution of this chapter is to explore how business cycles are amplified and transmitted within the economy and across borders when

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[1]See for example Bayoumi and Melander (2008), Adrian and Shin (2010) and Adrian *et al.* (2010a).

frictions in financial intermediation entail procyclicality in lending standards.[2]

The macroeconomic implications of changes in the value of assets held by financial intermediaries depend on whether they adjust the liabilities side of their balance sheets and on the reaction of their creditors. Under a passive attitude, a negative relationship between the market value of their assets and the leverage ratio (i.e. the ratio of assets to own capital) would emerge, as it is the traditional finding for households, and there would be little effects in terms of aggregate credit or other macro variables. However, this seems not to be the usual behavior of financial intermediaries. According to evidence in Adrian and Shin (2010) financial institutions manage actively their balance sheets in response to changes in prices and measured risk: commercial banks show almost constant leverage ratios over the cycle and market-based financial institutions (e.g. investment banks, hedge funds, etc.) display "procyclical" leverage, in the sense that during expansions both assets and leverage rise. This is consistent with the extended use of value-at-risk rules (VaR hereafter) by institutions and regulators, and with maximizing the return on equity in the context of an implicit maximum leverage permitted by creditors.[3] In this context, when asset prices are rising and measured risk is decreasing, financial intermediaries find themselves with excess capital. The way of adjusting, consistent with maximizing return on equity and VaR rules, is by expanding their balance sheets: on their liabilities side, issuing more sort-term debt and, on the assets side, expanding credit, that is, searching for potential borrowers. With good borrowers already served, the expansion of balance sheets of the financial sector as a whole is only possible by relaxing lending standards (e.g. requiring less collateral) and extending credit to projects that were previously denied access. In the downswing, the opposite happens.[4]. On aggregate, this balance sheet management by individual financial institutions contributes to the procyclical behavior of lending standards and credit. Other factors signaled in the literature as inducing procyclicality in lending standards include incentive

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[2]Along this chapter, "lending standards" refer to any of the various non-price terms specified in a line of credit or loan, such as collateral requirements, covenants, loan limits, etc. In the models outlined later, lending standards refer more precisely to the degree pledgeability of collateral (or "collateral price" as referred in Kiyotaki and Moore 2002).

[3]See Adrian and Shin (2008b) for a theory of financial leverage as a function of the shift in the risks inherent un the underlying environment.

[4]The same cyclical behavior emerges as creditors of financial intermediaries change the implicit maximum leverage permitted due to, for example, changes in measured risk. As creditors reduce "haircuts" on instruments such as repurchase agreements ("repos"), financial institutions face a rise in the implicit maximum leverage permitted in collateralized borrowing (among institutions or with ultimate non-financial creditors).

problems, herd behavior, accounting rules, etc.[5] In turn, this cyclical behavior of credit standards has aggregate effects on asset prices and on macroeconomic aggregates (Brunnermeier *et al.* 2009 and Adrian *et al.* 2010a), and on international capital flows (Shin 2009).

To explore the implications of cycles in lending standards I use a dynamic one-good small open economy model in which domestic agents face time-varying collateral constraints that limit their ability to leverage foreign debt on domestic asset holdings. The presence of financial frictions is a crucial ingredient: In a Modigliani-Miller world leverage would be irrelevant. Although I do not model the financial intermediation sector explicitly, the constraint linking borrowers and creditors in the model suggests frictions at both ends of financial intermediation: As in Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Aiyagari and Gertler (1999), limited enforcement caps the amount that intermediaries are willing to lend to a fraction of the market value of borrowers's assets. But differently from those models, the fraction imposing a ceiling on the leverage ratio of ultimate borrowers is not fixed but varies over the cycle. I interpret those variations as tightening (easing) in lending standards due for instance to contractions (expansions) of aggregate balance sheets of financial intermediaries, that is, to variations in financial market liquidity. The purpose of allowing the tightness of collateral constraints to vary over time is to combine, in a simple way, a credit supply channel as sketched in Adrian and Shin (2009) with the borrower's creditworthiness channel in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). I find that the procyclical behavior of lending standards amplifies shocks to fundamentals beyond the effect attributable to the financial accelerator mechanism. I interpret this extra amplification as resulting from the interaction of financial constraints in the lending and in the borrowing side of financial intermediation. The propagation mechanism operates through asset prices: procyclical lending standards reinforce the "overreaction" of asset prices to shocks signaled by Aiyagari and Gertler (1999). Moreover, the amplification effect is found to be bigger the more leveraged the economy is on average.

While there seems to be a consensus on the fact that financial systems are inherently subject to cycles, it is not yet clear how policymakers and regulators should intervene to mitigate these cyclical effects. In policy circles, the main focus

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[5]See for instance Borio *et al.* (2001) and Jiménez and Saurina (2006).

is placed on reforming financial regulation and on coordinating micro-prudential (i.e. institution-level) regulation with macro-prudential (i.e. system-wide) regulation.[6] Some of the proposed modifications include changes to mark-to-market procedures, the implementation of countercyclical capital charges and longer horizons for loan loss provisions. Understanding better the macro-financial linkages in the economy, within and across countries, is crucial for this discussion. Although the model used in this chapter is highly stylized, it contributes to the policy debate by exploring what can be the stabilizing effects of implementing policies aimed at lowering the degree of procyclicality in lending standards. In this sense, the results from the model simulations suggest the potential for sizable gains in terms of macroeconomic volatility from introducing some "macro-prudential" regulation that reduces the procyclicality of credit standards. For instance, a reduction in the correlation of the loan-to-value ratio with output from 0.45 to 0.25 in the model is associated with a drop in the volatility or real consumption of approximately one fourth. Also, the procyclical behavior of lending standards is found to contribute significantly to the persistence of business fluctuations.

This chapter is related to a recent macroeconomic literature with financial frictions incorporating perturbations that originate in the financial sector of the economy. Benk *et al.* (2005) introduce credit shocks in a monetary business cycle model with a cash-in-advance constraint and suggest that these shocks contributed significantly to US GDP movements. Kiyotaki and Moore (2008) interpret variations to the amount of equity holdings that entrepreneurs can resell as liquidity shocks and study how these affect aggregate output and asset prices in a monetary model. Focusing on the cyclical properties of firms' equity and debt payouts, Jermann and Quadrini (2009) use a model in which the firms' ability to borrow is limited by enforcement constraints and the tightness of the friction is subject to random disturbances, which are interpreted as shocks affecting directly the financial sector of the economy. Gruss and Sgherri (2009) also introduce fluctuations in the tightness of borrowing limits but on households debt and in the context of a two-country two-good model. Similar to this chapter, the focus is on the procyclical behavior of leverage limits and its effect on the volatility of macroeconomic aggregates and external imbalances. In this chapter the model is kept very parsimonious as it is meant mainly to explore the transmission mechanism. As in all the mentioned

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[6]See for example Borio *et al.* (2001) and Brunnermeier *et al.* (2009).

studies, the model treats financial intermediaries largely as a veil. Gertler and Kiyotaki (2010), instead, incorporate financial intermediaries explicitly and assumes that the quality of their assets follows an exogenous process to introduce fluctuations in their balance sheets. The model assumes a financial friction between intermediaries (inter-bank market) and with depositors, but the relationship with ultimate non-financial borrowers is frictionless. Instead, I interpret the presence of collateral constraints with cyclical tightening of margins in the model as deriving form frictions at both ends of financial intermediation, as suggested in Adrian and Shin (2010).

The structure of the chapter is as follows. Section 3.2 reviews the empirical evidence on the cyclical behavior of lending standards and the link with business cycles. Section 3.3 develops a small open economy model with procyclical lending standards and Section 3.4 shows the results of several numerical experiments aimed at exploring the implications of such behavior of lending standards on asset prices and real variables. Section 3.5 draws conclusions and highlights lines for future research.

3.2   Empirical Evidence on Lending Standards

In this section I review evidence from the empirical literature on the procyclical behavior of credit conditions and its implications for asst prices and macroeconomic variables, for different countries and periods. Several empirical studies have been looking into the cyclical behavior of capital buffers of financial institutions, aggregate liquidity and lending standards, and their relationship with aggregate fluctuations. There seems to be conclusive evidence that credit conditions not only vary over the cycle but also behave procyclically and that this behavior has aggregate implications for asset prices and real activity. One explanation for that cyclical behavior relies on information asymmetries between borrowers and lenders.[7] Other many studies identify changes in aggregate credit conditions with balance sheet management by financial intermediaries, due for instance to the prescriptions of internal risk-management models, to risk-sensitive capital regulations

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[7]In a setting where banks obtain private information about their clients' creditworthiness, Dell'Ariccia and Marquez (2006) show that banks may loosen lending standards when information asymmetries vis-à-vis other banks are low.

(e.g. prescriptions in Basel II) or to the use of backward-looking loan-loss provision practices.[8]

Adrian and Shin (2009) make emphasis on the fact that a substantial fraction of the financial system is composed of highly leveraged intermediaries that fund themselves using market instruments, such as repurchase agreements ("repos" and "reverse repos") and that hold assets that are marked-to-market and are then very sensitive to variations in asset prices and in measured risk. They argue that the procyclical behavior of the financial system is then due to frictions in the supply of credit. Adrian and Shin (2010) document that financial intermediaries manage their balance sheets actively in such a way that their leverage ratio is procyclical, i.e. high during booms and low during busts. Specifically, instead of adjusting equity, they react to changes in asset prices that affect their net worth and to changes in measured risk by issuing more short-term debt and accumulating more assets. This is consistent with their models of risk and in particular with the use of VaR rules, which dictate adjusting exposures continuously so that the probability of default is kept constant. Indeed, Adrian and Shin (2010) show evidence suggesting that measures of VaR explain shifts in total assets, leverage and key components on the liability side of the balance sheet, such as stock of repos. Adrian and Shin (2008a, 2009) find that the procyclicality of leverage is much clearer for market-based intermediaries (such as security dealers and brokers) than for the case of commercial banks and highlight the importance of those institutions and, more broadly, of the "shadow banking" (including asset-backed securities issuers, finance companies and funding corporations), in conveying information on the credit conditions ruling in the economy.

Ayuso *et al.* (2004) find a significant negative relationship between business cycle and banks' capital buffers in Spain from 1986 to 2000. Given that they focus their attention on voluntary capital buffers, they argue that the cyclical pattern is due to factors which are beyond the inherent features of risk-sensitive bank capital regulation, such as Basel II. Also for the Spanish economy but using loan-by-loan information from 1984 to 2002, Jiménez and Saurina (2006) show that collateral requirements are relaxed during boom periods while the opposite happens during recessions. Asea and Blomberg (1998) look at the contract terms of loans granted

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[8]See Borio *et al.* (2001) for a discussion of the role of risk measurement by individual institutions and its implications for systemic risk and aggregate conditions.

by U.S. banks from 1977 to 1993 and find that there is a systematic tendency for lending standards to vary over the business cycle: during the upswing of the cycle the risk premia banks charge on loans decreases, loan size increases and the probability of requiring higher collateral decreases; the opposite occurs during the downswing of the cycle.

Adrian and Shin (2008a) and Adrian *et al.* (2010a) provide evidence that the procyclical behavior of financial intermediaries' leverage has an impact on aggregate financial conditions and in real economic outcomes, especially on components of GDP that are particularly sensitive to credit supply. Adrian *et al.* (2010a) highlight the relevance of asset prices and the market risk premia in the transmission mechanism. Consistent with this evidence and using data from the U.S., Bayoumi and Melander (2008) document that during periods when the capital-asset ratio is increasing there is a net easing of lending standards (i.e. an increase in credit supply given borrower characteristics). They also find that a tightening of loan standards causes the quantity of credit effectively to decline. Lown and Morgan (2006) use survey data on credit standards from U.S. banks and find that commercial credit standards are highly significant in predicting commercial bank loans, real GDP and inventory investment. Their variance decomposition results indicate that innovations in lending standards account for nearly a third of the error variance in output at 1 year horizon, more than the fraction attributable directly to the federal funds rate.

There is evidence of procyclicality in financial conditions also in studies using cross country data. For example, Mendoza and Terrones (2008) have examined the dynamics of both macro aggregates and firm-specific financial indicators during "credit boom" episodes. Using cross-country data for 48 industrial and emerging countries from 1960 to 2006, they find that credit booms are associated with periods of economic expansion, rising equity and housing prices, and widening external deficits. Evidence of procyclicality also shows up from firm level data: the credit boom—and the macroeconomic upswing that accompany them—coincide with higher leverage, firm value and use of external financing by firms. Bank data too appear consistent with procyclical lending standards: ratios of capital adequacy and non-performing loans seem to decrease during credit booms.

Gruss and Sgherri (2009) also present evidence on the behavior of firms' leverage,

using data from 16 advanced and 12 emerging European economies over the period from January 1999 until April 2008. The evidence from that sample confirms, first, that firms' leverage ratios vary substantially over the cycle. Next, and relying on financial condition indices constructed by means of country-specific vector autoregression models and corresponding impulse responses functions, they find that changes in financial conditions account for a large fraction of the variation in GDP growth, especially in the emerging countries in the sample. Also, a higher degree of procyclicality in firms' leverage is found to be associated with higher volatility in private investment. Finally, evidence in Gruss and Sgherri (2009) suggest that changes in firms' borrowing tend to be more sensitive to changes in asset prices in those economies where firms leverage co-moves more closely with the business cycle, which can be interpreted as economies where the financial frictions are stronger.

Although evidence of procyclicality on lending conditions is also found for periods excluding the recent financial crisis,[9] the explosive growth in securitization that modified the model of financial intermediaries from "risk warehousing" to "originating and distributing" has been signaled as a factor accentuating relaxation of standards in the last credit cycle. Keys *et al.* (2010) find that securitization practices in the U.S. subprime market did adversely affect the screening standards of lenders: loans more likely to be securitized default 20% more than similar risk profile loans with lower likelihood of securitization. Mian and Sufi (2009) use detailed ZIP code-level data from the U.S. and argue that the rise in securitization of subprime mortgages represented an outward shift in mortgage credit by lenders, which came along with the relaxation of earlier credit-rationing constraints.

Regarding the international implications of financial factors, some authors claim that the expansion of financial intermediaries' balance sheets and the growing use of securitization had a significant impact on international capital flows. Shin (2009) argue that the increased leverage of the financial system in the U.S., fueled by securitization, exacerbated global imbalances. He shows evidence that foreign central banks have been a particularly important funding source for residential mortgage lending in the United States. Shin (2009) argues that the fact that the greatest increase in foreign holdings of U.S. debt securities has been on

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[9]For example Adrian *et al.* (2010a) repeat their estimations with data up to the crisis and the results are similar. Other studies, such as Bayoumi and Melander (2008) and Lown and Morgan (2006), use data prior to the crisis.

asset-backed securities issued by private label securitization vehicles suggests an alternative "supply push" perspective to global imbalance that complements the "savings glut" hypothesis.[10]

3.3 A Small Open Economy Model

In this section I use a production small open economy model with financial frictions, similar to the one in Kocherlakota (2000), to analyze how the amplification of business cycles is affected when lending standards vary over the cycle. Output is produced using a constant returns to scale technology, using a durable good in fix supply (for example, land or real estate) and a durable good in variable supply (that I call capital). The economy is populated by a continuum of identical, infinitely-lived and self-employed firm-households, with preferences described by:

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \ln c_t \ , \qquad 0 < \beta < 1 \tag{3.1}$$

where c_t denotes consumption and β is the subjective discount factor. The budget constraint faced by the representative agent is:

$$c_t + q_t \left(L_{t+1} - L_t \right) + (1+r)d_t + k_{t+1} - (1-\delta)k_t = d_{t+1} + y_t \ , \tag{3.2}$$

where L_t denotes the individual holdings of the asset in fixed supply (land), q_t is its relative price in terms of the consumption good, k_t denotes holdings of capital and δ its depreciation rate per period. Output (GDP) is given by $y_t = A_t k_t^\alpha L_t^{1-\alpha}$ where A_t is stochastic total factor productivity (TFP) and $0 < \alpha < 1$. Financial markets are incomplete: d_{t+1} is the amount of non-contingent debt issued at t and r is the real interest rate the economy faces in international markets, taken as given by individual agents and assumed constant for simplicity. As will be clear later, the values assumed for β and r will imply that the small open economy is relatively impatient in comparison to international markets.

In the production function land is combined with another durable good (capital) instead of labor, so that agents have an additional instrument, besides debt,

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[10]See, for example, Caballero *et al.* (2008).

that is subject to financial frictions, to transfer resources across periods.[11] However and in order to focus on the main transmission mechanisms, the model is kept as parsimonious as possible, so it does not include capital adjustment costs.

Financial frictions.   The world credit market is assumed to be imperfect: Due to an inability to commit to repayment, agents in the small open economy need to guarantee their debt by offering the domestic assets as collateral. The collateral credit constraint takes the form of the margin requirement proposed by Aiyagari and Gertler (1999) and used in a small open economy context by Kocherlakota (2000) and Mendoza (2010), among others. As in Kocherlakota (2000), Iacoviello (2005) and Mendoza and Smith (2006), the asset used for collateral is in fix supply. Specifically, the endogenous credit constraint that agents face is given by:

$$d_{t+1} \le \varphi_t q_t L_{t+1} \tag{3.3}$$

where φ_t determines the maximum amount that can be borrowed for a given value of collateral at time t, imposing a ceiling on the loan-to-value ratio ("LTV ratio" hereafter). The maximum leverage of the borrower, that is, the ratio of assets to net worth, is given by $1/(1 - \varphi_t)$. The "collateral price" of the asset is a fraction of the market price of the asset, as in Kiyotaki and Moore (1997, 2002), but here it is assumed to be time varying.

Evidence in Adrian and Shin (2010) and Adrian *et al.* (2010a) suggests the presence of financial frictions in the funding side of financial intermediation; that is, between financial intermediaries and between financial institutions and ultimate non-financial lenders. According to the authors, changes in underlying conditions such as measured risk, asset prices, the opportunity cost of funds, etc. translate into variations in their ability to leverage their liabilities into assets and ultimately into changes in the aggregate supply of credit. Shifts in the size of financial intermediaries' balance sheets and in aggregate credit supply come along with changes in the quality of the marginal credits, implying variations in lending standards (Bayoumi and Melander 2008).

I integrate this friction in the model, in an admittedly crude way, by allowing

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[11]Production is similar then to Kocherlakota (2000) but relaxing the full depreciation assumption.

the ceiling on the leverage ratio of borrowers $1/(1 - \varphi_t)$ to vary over time. In this sense, an increase in φ_t implies a higher allowed leverage for the borrower: lenders would allow more borrowing for any given value of collateral. What I am trying to capture in a simple way is an exogenous force, possibly correlated with the business cycle, that affects credit supply for any given level of net worth of borrowers. As a starting point, I simply assume that TFP and the LTV ratio jointly follow a first-order bivariate autoregressive process in the neighborhood of the constant unconditional mean ($\bar{A}$ and $\bar{\varphi}$). In this sense, the approach is similar to other models that introduce shocks that are interpreted as originated in the financial sector, such as Kiyotaki and Moore (2008) and Jermann and Quadrini (2009), among others. More precisely, I assume:

$$\begin{pmatrix} ln(A_t) - ln(\bar{A}) \\ ln(\varphi_t) - ln(\bar{\varphi}) \end{pmatrix} = \begin{pmatrix} \rho_A & 0 \\ 0 & \rho_\varphi \end{pmatrix} \begin{pmatrix} ln(A_{t-1}) - ln(\bar{A}) \\ ln(\varphi_{t-1}) - ln(\bar{\varphi}) \end{pmatrix} + \begin{pmatrix} \epsilon_{A,t} \\ \epsilon_{\varphi,t} \end{pmatrix} , \quad (3.4)$$

where the vector of shocks $\epsilon_t = (\epsilon_{A,t}, \epsilon_{\varphi,t})'$ follows a bivariate normal distribution with zero mean and contemporaneous variance-covariance matrix V, given by:

$$V = \begin{pmatrix} \sigma_A^2 & cov(A, \varphi) \\ cov(A, \varphi) & \sigma_\varphi^2 \end{pmatrix}. \quad (3.5)$$

Equilibrium Given initial values of debt, capital and land holdings, the representative Household-Firm problem is to choose sequences $\{c_t, k_{t+1}, d_{t+1}, L_{t+1}\}$, taking q_t, φ_t, A_t and r as given, in order to maximize (3.1), subject to equations (3.2) and (3.3). Land is assumed to be in aggregate fixed supply and normalized to one. Imposing this market clearing condition and letting μ_t be the multiplier on the borrowing constraint, the optimality conditions for the representative agent's problem include:

$$U_{c,t} = \beta \mathrm{E}_t U_{c,t+1}(1 + r) + \mu_t \quad (3.6)$$

$$U_{c,t} = \beta \mathrm{E}_t U_{c,t+1} \left[\alpha A_{t+1} k_{t+1}^{\alpha-1} + (1 - \delta) \right] \quad (3.7)$$

$$q_t \left[U_{c,t} - \varphi_t \mu_t \right] = \beta \mathrm{E}_t U_{c,t+1} \left[q_{t+1} + (1 - \alpha) A_{t+1} k_{t+1}^\alpha \right] \quad (3.8)$$

If the borrowing constraint were not binding, μ_t would be zero and Equation (3.6) would be a standard Euler equation for debt. However, given the assumptions on the subjective discount factor β and the international interest rate r, in a deterministic steady state μ is strictly greater than zero and, hence, (3.3) holds with

equality. The extent to which this is also the case in a stochastic equilibrium (i.e. outside the steady state) mainly depends on the size of the gap between β and $1 + r$ and the variance of the shocks hitting the economy. In this chapter, as in Iacoviello (2005), Iacoviello and Neri (2010) and Jermann and Quadrini (2009) among others, the variability of shocks is kept "small enough" relative to the degree of impatience and the model is solved by linearizing around the steady state with a binding collateral constraint.[12]

The presence of the financial friction implies, from Equation (3.6), that agents in the domestic economy always face an endogenous external financing premium on the effective (i.e. shadow) real interest rate at which they borrow. This can be appreciated by rewriting (3.6) as:

$$1 = \beta \mathrm{E}_t \frac{U_{c,t+1}}{U_{c,t}} \left[\frac{(1 + r)}{1 - \mu_t / U_{c,t}} \right]$$

As long as the economy is constrained (i.e. $\mu_t > 0$), the effective interest rate $\frac{(1+r)}{1-\mu_t/U_{c,t}}$ is higher than $(1 + r)$. The higher effective interest rate reflects the fact that, at the prevailing interest rate $(1+r)$, agents in the domestic economy would like to borrow more than they are actually allowed to.

Finally, solving Equation (3.8) forward we can obtain a standard asset pricing condition for land:

$$q_t \;=\; \mathrm{E}_t \sum_{j=0}^{\infty} \left(\prod_{i=0}^{j} \Lambda_{t+i,t+1+i} \right) r^L_{t+1+j} \tag{3.9}$$

where $\Lambda_{t,t+1} = \beta U_{c,t+1}/(U_{c,t} - \varphi_t \mu_t)$ is the stochastic discount factor and $r^L_t = (1-\alpha)A_t k_t^{\alpha}$ is the marginal product of land. The valuation of the asset corresponds to the discounted flow of future returns.[13]

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[12]In the quantitative exercises in the next sections I check that indeed the value of the multiplier μ_t is always positive.

[13]Note that $\Lambda_{t,t+1}$ includes both the multiplier μ_t and the LTV ratio φ_t, none of which would appear in a frictionless model.

3.3.1 The Role of Asset Prices and Excess Returns

To understand the role of asset prices in shaping equilibrium dynamics, it is useful to derive an expression for excess returns (i.e. risk premium) in this model and explore how it is affected by the fact that the economy is financially constrained and that the tightness of the constraint (i.e. the LTV ratio) varies over time. The return on holding land is defined as $R_{t+1}^L \equiv \left(\frac{r_{t+1}^L + q_{t+1}}{q_t} \right)$. Using the Euler equations for bonds and land we can express the excess return on land holdings (relative to the real interest rate on international debt) as:

$$\mathrm{E}_t(R_{t+1}^L) - (1+r) = \frac{-cov(U_{c,t+1}, R_{t+1}^L)}{\mathrm{E}_t U_{c,t+1}} + \frac{\mu_t \left(1 - \varphi_t\right)}{\beta \mathrm{E}_t U_{c,t+1}} \qquad (3.10)$$

If the collateral constraint is binding ($\mu_t > 0$), then there is a positive *wedge* between the equity premium in this economy and the "fundamental" one—that is, the one that would prevail in a frictionless environment. Indeed, if the collateral constraint is not binding ($\mu_t = 0$), then Equation (3.10) would reduce to $\frac{-cov(U_{c,t+1}, R_{t+1}^L)}{\mathrm{E}_t U_{c,t+1}}$, which is the standard excess return corresponding to a frictionless asset-pricing model, the "fundamental" risk premium (Aiyagari and Gertler 1999).

In turn, the behavior of excess returns, and of the wedge to its "fundamental" expression, affects asset prices. Taking expectations on the return on land holdings R_{t+1}^L and solving for q_t and iterating forward, we obtain:

$$q_t = \mathrm{E}_t \sum_{j=0}^{\infty} \left(\prod_{i=0}^{j} \frac{1}{\mathrm{E}_t(R_{t+1+i}^L)} \right) r_{t+1+j}^L \qquad (3.11)$$

where the sequence $\{\mathrm{E}_t(R_{t+1+j}^L)\}_{j=0}^{\infty}$ is given by (3.10). It should thus be clear that an increase of excess returns at period t (or at any other time in the future) would increase the rate at which future dividends are discounted, thereby lowering the price of the asset at period t.

The behavior of excess returns (as well as the one of the wedge between the actual and the "fundamental" risk premium) plays an important role in the dynamics of the model. As Aiyagari and Gertler (1999) and Mendoza and Smith (2006) point out, the behavior of the equity premium is affected both directly and indirectly by the presence of financial market frictions. A binding collateral constraint in the current period affects directly the wedge between the "fundamental" and the

actual equity premium, as indicated by the second term of equation (3.10). For example, a tighter borrowing constraint (higher μ_t) in period t originated by a drop in productivity that lowers asset prices would reinforce such a drop by pushing up the risk premium. Regarding the indirect effect, the probability that the constraint will be binding in the future affects the covariance expression in the first term of equation (3.10). The possibility of a tighter borrowing constraint in period $t+1$ is likely to reduce (i.e., make more negative) the covariance with the marginal utility of consumption in $t+1$. In other words, the more stringent the borrowing constraint, the bigger the drop in consumption at $t+1$ (i.e., the rise in $U_{c,t+1}$) associated with a given fall in the ex-post return on equity.

The presence of effects due to financial frictions can hence amplify fluctuations of the equity premium and, thereby, of equity prices, as it was shown by Aiyagari and Gertler (1999). What is new in this model is that this phenomenon may be potentially affected by fluctuations in lending standards (i.e. in φ_t). In the following sections I analyze how time-varying lending standards affect the reaction of asset prices and the amplification of shocks relying on numerical experiments.

3.3.2   Parameter Values and Solution Method

To perform numerical experiments with the model it is necessary to assign values to 10 parameters. Most of them are standard preference and technology parameters for which I use reasonably conventional values, reported in Table 3.5. The period in the model is a year. The parameter $\bar{A}$ is set to normalize output to one in the non-stochastic steady state. The rate of time preference is assumed to be bigger than the gross international real interest rate ($1 + r < 1/\beta$). Given this assumption, in a deterministic steady state μ is strictly greater than zero and, hence, Equation 3.3 holds with equality and the economy is a net debtor in international markets.

The only parameters specific to my model are the ones related to the law of motion of the LTV ratio: $\bar{\varphi}$, ρ_φ, σ_φ and $cov(A, \varphi)$—or, equivalently, the correlation between innovations to TFP and the LTV ratio, that I denote $\rho_{(A,\varphi)}$. Regarding the long-run mean of the LTV ratio ($\bar{\varphi}$), I use a range of values from 0.3 to 0.7 (see Table 3.5) that imply a ceiling on the leverage ratio of ultimate borrowers ranging from 1.4 to 3.3. As a reference, Calza *et al.* (2007) consider LTV ratios ranging

from 50% to 90% to analyze the effect of different institutional characteristics of mortgage markets, 50% being the LTV ratio estimated for the Italian market. Jermann and Quadrini (2009) report that the average LTV ratio for nonfinancial companies over the period 1984 to 2008 is 0.46. Mendoza (2010) uses values of 0.2 and 0.3 for the LTV ratio.

The persistence parameter of the LTV ratio ρ_φ is set to 0.6, the same than for productivity shocks. I also report the results when shocks to TFP and to lending standards are iid. The standard deviation of innovations to the LTV ratio (σ_φ) is set to 5%, 2.5 times bigger than the standard deviation of innovations to productivity. The correlation of innovations to TFP and the LTV ratio, $\rho_{(A,\varphi)}$, is a key parameter for the policy experiment explained later in Section 3.4.3. For this parameter I use a range of values from 0.8 to 0. These parameter values are overall consistent with the empirical evidence in Section 3.2 and with estimates in Jermann and Quadrini (2009).[14]

Numerical solution technique. The methods are familiar: The model is solved by log-linearizing the equations characterizing the equilibrium around the deterministic steady state (with Equation 3.3 holding with equality) and by solving the resulting system of linear difference equations to obtain the policy functions. As explained above, the parameters imply that the collateral constraint is assumed to be binding in the steady state. This implies that the amplification created by the financial friction is symmetric and is always present (like, for example, in Iacoviello 2005, Iacoviello and Neri 2010, Calza *et al.* 2007 and Jermann and Quadrini 2009).[15]

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[14]Jermann and Quadrini (2009) estimate a first-order bivariate autoregressive process for productivity and financial shocks, where the financial shock series is constructed using a model's optimality conditions. Using quarterly data, the estimated autocorrelation parameters of the shocks are 0.93 and 0.97 respectively, the off-diagonal elements are found to be close to zero, the estimated standard deviation of financial innovations are 2.5 bigger than the one of productivity innovations and the estimated correlation of shock innovations is 0.36.

[15]Note that if the focus were on the effect of occasionally-binding constraints, as it is the case in Mendoza (2010), this solution technique would probably lead to a poor approximation, as it would fail to capture the non-linear dynamics produced when the economy switches from a state in which the constraint does not bind to a state in which it binds.

3.4 Quantitative Analysis

3.4.1 The Usual Financial Accelerator Mechanism

Before introducing fluctuations in lending standards, this section shows the response of the model when the leverage ratio does not vary over time. The amplification of shocks due to financial frictions such as in (3.3) when the LTV ratio is a fixed parameter has been widely analyzed in the literature (some examples include Bernanke and Gertler 1989, Kiyotaki and Moore 1997, 2002 and Kocherlakota 2000). In this section I analyze the workings of the financial accelerator mechanism in the context of this model.

Figure 3.1 shows the reaction of consumption, investment, output, debt, net exports-to-GDP and asset prices to a negative 1% productivity shock. The different lines in each plot correspond to different $\bar{\varphi}$ values, that is, different long-run averages for the LTV ratio, ranging from 0.3 to 0.7. The first result to notice is that the more leveraged the economy is (i.e. the higher $\bar{\varphi}$), the stronger the response of asset prices and real variables to the shock. The drop in debt in the period following the shock reflects the decreased ability to rollover debt due to the drop in the market value of the collateral after the productivity decline. While $\hat{d}_t$ is slightly higher than -0.2% when $\bar{\varphi} = 0.3$, it drops by almost 0.6%, three times more, when $\bar{\varphi} = 0.7$.[16] The counterpart of the sudden inability to rollover debt is the capital outflows captured by the reaction of net exports-to-GDP: The trade balance jumps up by 1% when the long-run leverage is low ($\bar{\varphi} = 0.3$), while the same shock to productivity triggers a 5% increase in net experts-to-GDP when the economy is highly leveraged ($\bar{\varphi} = 0.7$). The response on impact of consumption is of slightly less than 0.8% when the long-run LTV ratio is 0.3, but it is twice as big (1.6%) when $\bar{\varphi}$ is 0.7. The greater outflows under a high leverage setting are relatively more absorbed by investment in physical capital than by consumption: the drop in investment is around four times bigger when $\bar{\varphi} = 0.7$ than when $\bar{\varphi} = 0.3$, while this ratio for consumption is only two.[17] The drop in output reflects first the drop in productivity and then the decrease in the capital stock; $\hat{y}_t$ reaches a minimum of -1% when $\bar{\varphi} = 0.3$ and of -1.6% when $\bar{\varphi} = 0.7$.

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[16]Variables with hat denote log deviations from their steady state value.

[17]The model does not include capital adjustment costs. The presence of such costs would have implied a higher cost for smoothing consumption, leading to a bigger relative drop in consumption.
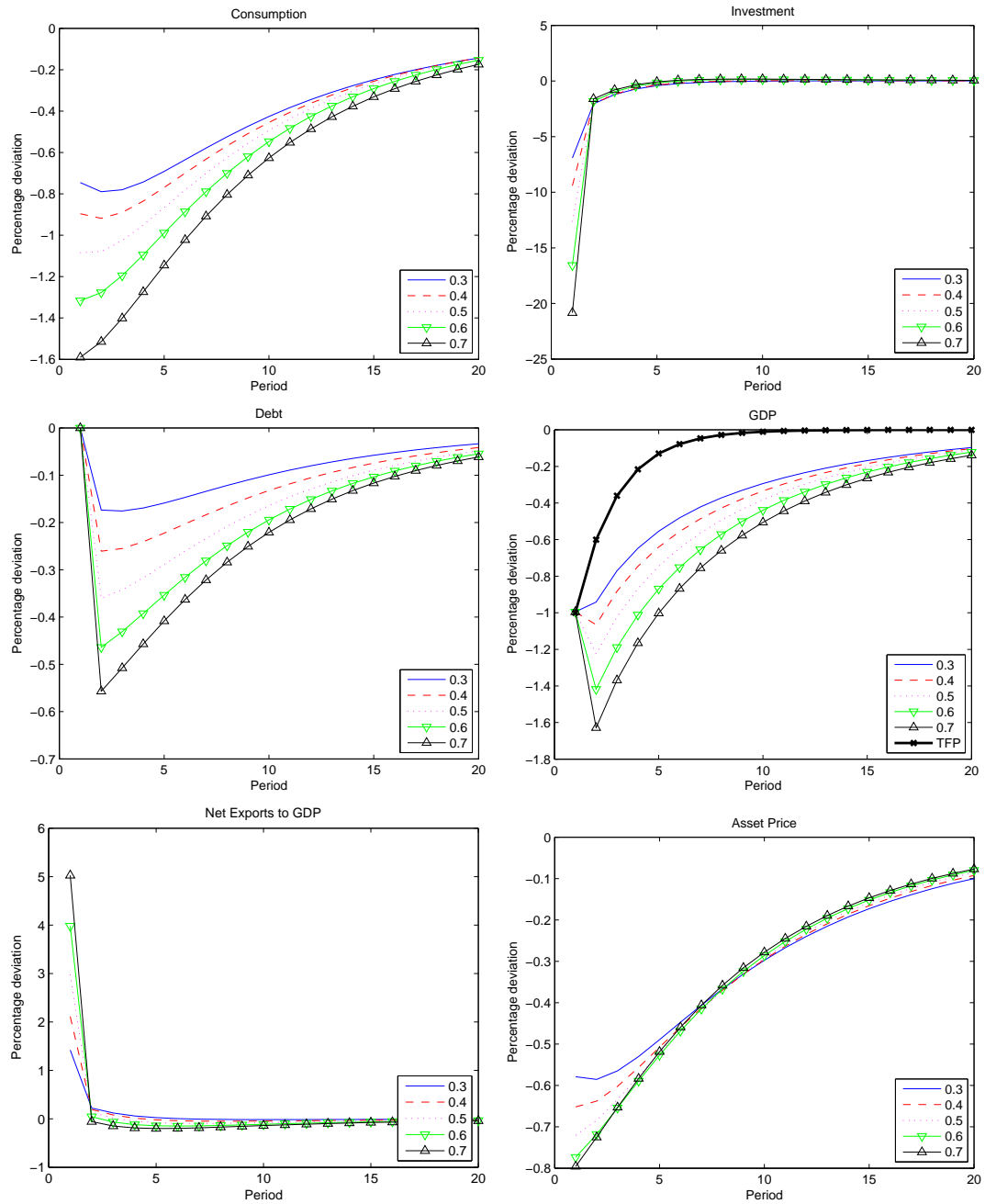
FIGURE 3.1: Impulse Responses to Productivity Shock.
Responses to a 1% negative shock to TFP under different values for the long-run
LTV ratio ($\bar{\varphi}$). All the responses are expressed in percentage deviation from the
steady state value, except for the net exports-to-GDP ratio that is in percentage
points.

Excess Returns and Asset Prices.   In the model the negative shock to income
cannot be smoothed out by borrowing because the drop in the asset price implies
a reduction in the market value of the collateral and the consequent reduction
in the borrowing capacity of the constrained economy. The drop in productivity
affects the asset price directly because it affects actual dividends and the expected
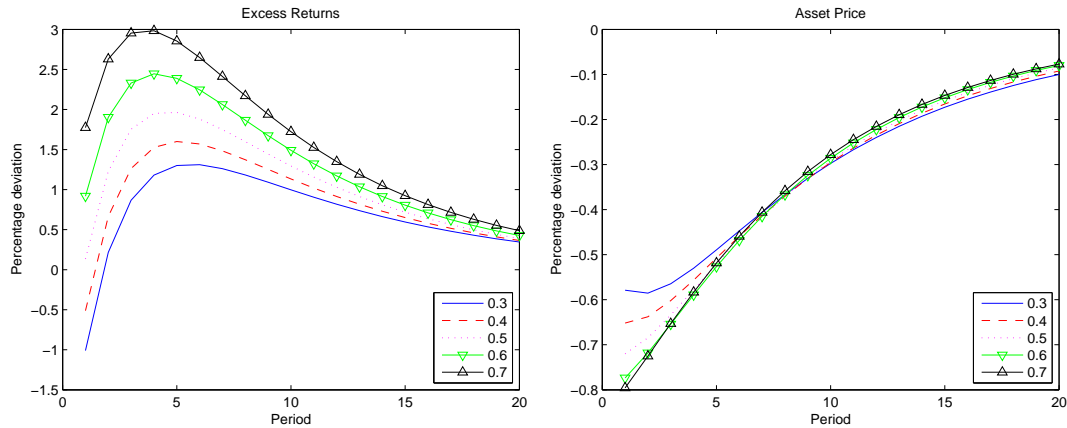
FIGURE 3.2: Excess Returns and Asset prices

Response of excess returns (equity premium) and asset prices to a 1% negative shock to TFP under different values for the long-run LTV ratio ($\bar{\varphi}$).

flow of future dividends (given that the shock is persistent).[18] But the shock also affects the asset price because of the financial friction in the economy. This effect, described as "overreaction" of asset prices to shocks in Aiyagari and Gertler (1999) and explained in Section 3.3.1, can in principle have different intensities for low and high leveraged economies. Table 3.1 reports the steady state values of excess

TABLE 3.1: Steady State Values

Loan-to-Value ($\bar{\varphi}$)	0.3	0.4	0.5	0.6	0.7
Excess Returns (%)	3.29	2.82	2.35	1.88	1.41
Asset Price	6.87	7.33	7.88	8.51	9.24

returns and the asset price for different values of the long-run LTV ratio ($\bar{\varphi}$). The steady state level of excess returns is lower the higher $\bar{\varphi}$, while the opposite is the case for asset prices. Figure 3.2 instead depicts the reaction of excess returns and asset prices starting from the steady state when the economy is hit by a 1% negative productivity shock. The risk premium drops on impact for the two lowest values of $\bar{\varphi}$ considered, 0.3 and 0.4, while it increases for the rest. In all cases the dynamics of the risk premium lay above the steady state level after the first period. While the steady state level of excess returns is decreasing in $\bar{\varphi}$, its response to productivity shocks is stronger for higher average LTV levels. For all the values of $\bar{\varphi}$ considered, the asset price decreases on impact when productivity

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[18]In Section 3.4.4 I repeat the exercise assuming iid shocks. Interestingly, the response of asset prices to productivity shocks is very persistent even when the shock is iid.

declines. The size of the decrease is increasing in $\bar{\varphi}$, implying that in this model the "overreaction" of asset prices is bigger the more leveraged the economy is. Given the 1% shock to TFP, the asset price drops less than 0.6% from its steady state value when LTV is 0.3 on average but it drops by 0.8% when $\bar{\varphi} = 0.7$.

3.4.2 The Effect of Shifts in Lending Standards

Along the previous section the LTV ratio was introduced as a constant. In this section instead I explore the response of the model to fluctuations in the LTV ratio. The empirical evidence cited in Section 3.2 suggests that expansions (contractions) of financial intermediaries' balance sheets lead to the easing (tightening) of lending standards. Although the model is not sufficiently rich to capture precisely this phenomenon, I interpret shocks to $\hat{\varphi}_t$ as relaxation/tightening in lending standards due to frictions between the financial sector and ultimate lenders, as discussed in Adrian and Shin (2010). Fluctuations in $\hat{\varphi}_t$ can also be interpreted as shocks to balance sheets of financial intermediaries due, for example, to changes in measured risk or to changes in the risk-appetite of investors and in the maximum leverage they allow to financial intermediaries.

Figure 3.3 shows impulse responses to a 1% decrease in the LTV ratio, that is, a tightening in lending standards. The different lines in each plot correspond to different $\bar{\varphi}$ values. As it was the case for shocks to productivity, the responses of asset prices and real variables to the shock are stronger when the LTV ratio fluctuates around a higher long-run level. The drop in debt issued reflects the combination of a lower leverage allowed by creditors (the drop in $\hat{\varphi}_t$) and the drop in the asset price triggered by the tightening of lending standards. When $\bar{\varphi} = 0.3$, the asset price drops to around 0.2% below its steady state value and $\hat{d}_t$ decreases by 0.4%. Instead, in a highly leveraged economy ($\bar{\varphi} = 0.7$) these drops are -0.6% and -1.2% respectively. The tightening in credit conditions forces agents to cut strongly on investment (between -9% and -35% depending on the mean leverage ratio) in order to smooth partly the drop in consumption (between -0.2% and -1%). The reduction in the capital stock implies a decrease in the marginal productivity of land and then a lower market value for the collateral, reinforcing the tightening of the borrowing constraint. Output is not affected on impact but only one period later, due to the reduction in the capital stock induced by a lower
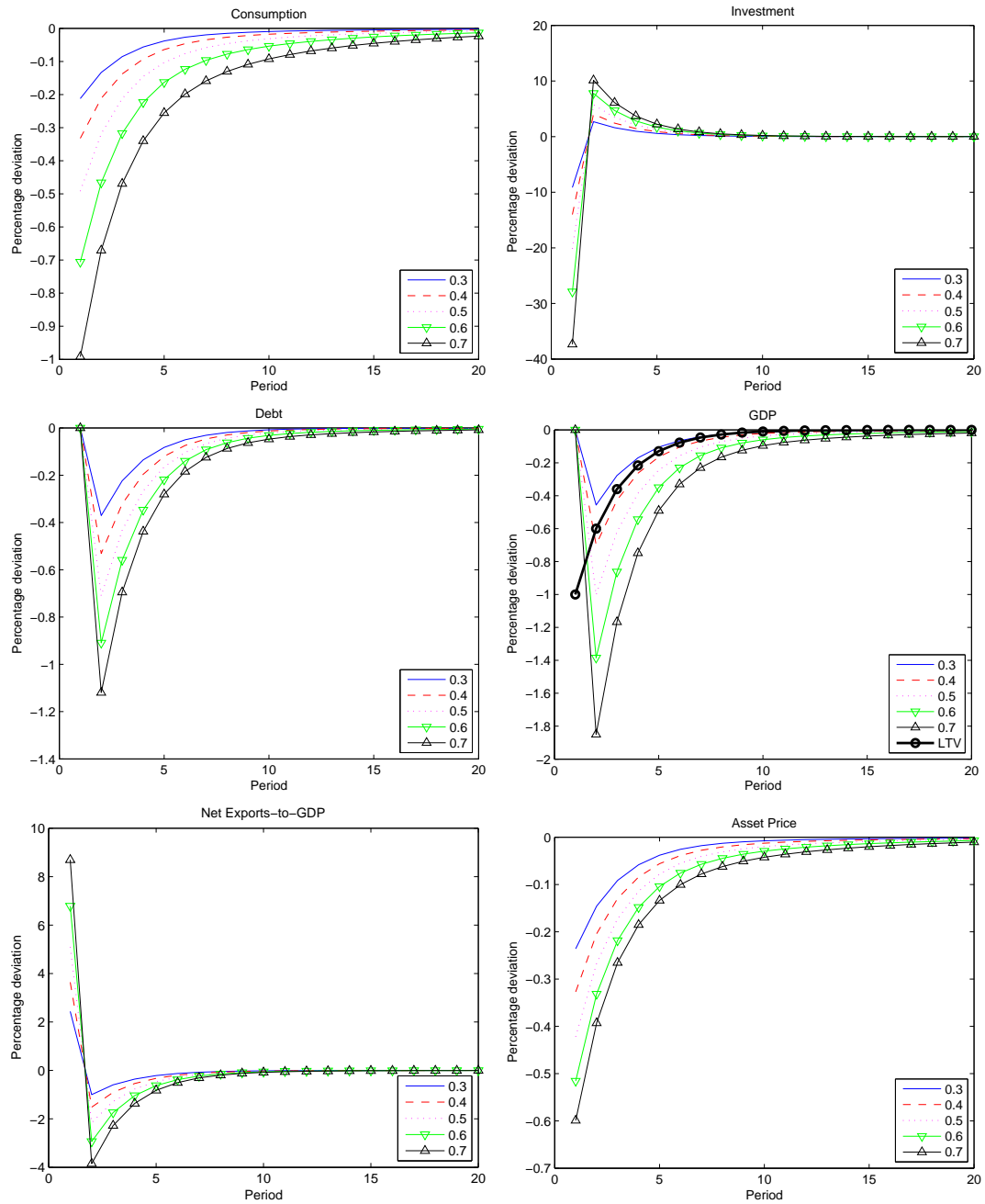
FIGURE 3.3: Impulse Responses to Lending Standards Shock.
Responses to a 1% negative shock to the LTV ratio under different values for the long-run LTV ratio ($\bar{\varphi}$). All the responses are expressed in percentage deviation from the steady state value, except for the net exports-to-GDP ratio that is in percentage points.

borrowing limit; under $\bar{\varphi} = 0.7$ GDP decreases by almost 2% with respect to its steady state value, one period after the shock.
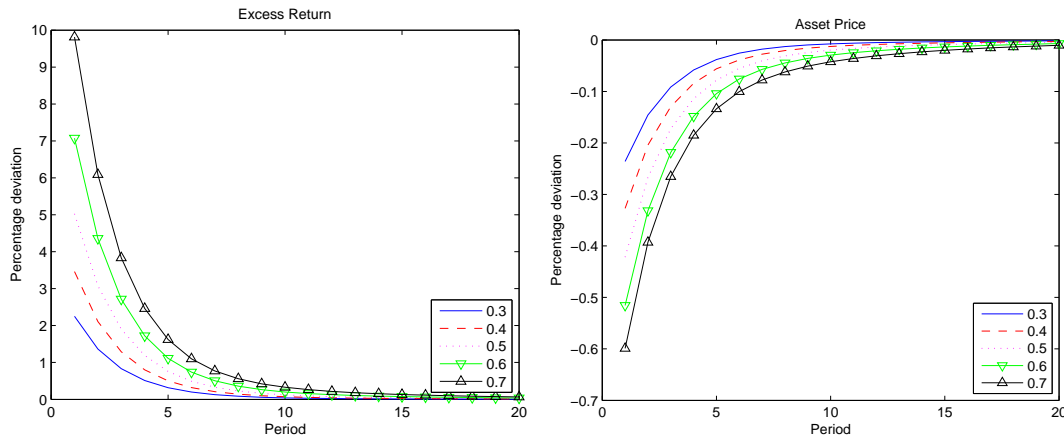
FIGURE 3.4: Excess Returns and Asset Prices

Response of excess returns (risk premium) and asset prices to a 1% negative shock
to the LTV ratio under different values for the long-run LTV ratio ($\bar{\varphi}$).

Excess Returns and Asset Prices.   Figure 3.4 reports the reaction of excess
returns and the asset price to the shock to lending standards. When φ_t drops, the
risk premium required by investors goes up and asset prices drop. The response of
both excess returns and the asset price is bigger the higher the long-run leverage
ratio of the economy: The rise in excess returns when $\bar{\varphi} = 0.3$ is 2%, but it is almost
five times bigger, 10%, when $\bar{\varphi} = 0.7$. The associated drops in q_t are approximately
0.2% and 0.6% respectively. The responses in Figure 3.3 and Figure 3.4 show that
the predictions of this simple model to changes in lending conditions attributable
to credit supply shocks is consistent with the evidence put forward by Adrian and
Shin (2010) and reviewed in section 3.2.

Procyclical Lending Standards.   What would happen then if lending stan-
dards behaved "procyclically"? We can obtain an intuitive answer by comparing
the responses of the same variables to a productivity shock on one side, and to a
combination of both the productivity shock and the lending standards shock (e.g.
a case in which the innovations to productivity and lending standards are perfectly
correlated) on the other side. The exercise is carried for a middle value of long-run
leverage: $\bar{\varphi}$ is set at 0.5, implying a leverage ratio equal to two. Figure 3.5 reports
the responses of consumption, investment, debt and output under a "fixed LTV"
ratio (i.e. only productivity shock) and "procyclical LTV" (i.e. under simultane-
ous productivity and lending standards shocks). The fourth graph in Figure 3.5
also depicts the path of $\hat{A}_t$ and $\hat{\varphi}_t$ under the "procyclical LTV" case. Both shocks
are assumed to have the same persistence, so under this case lending standards are
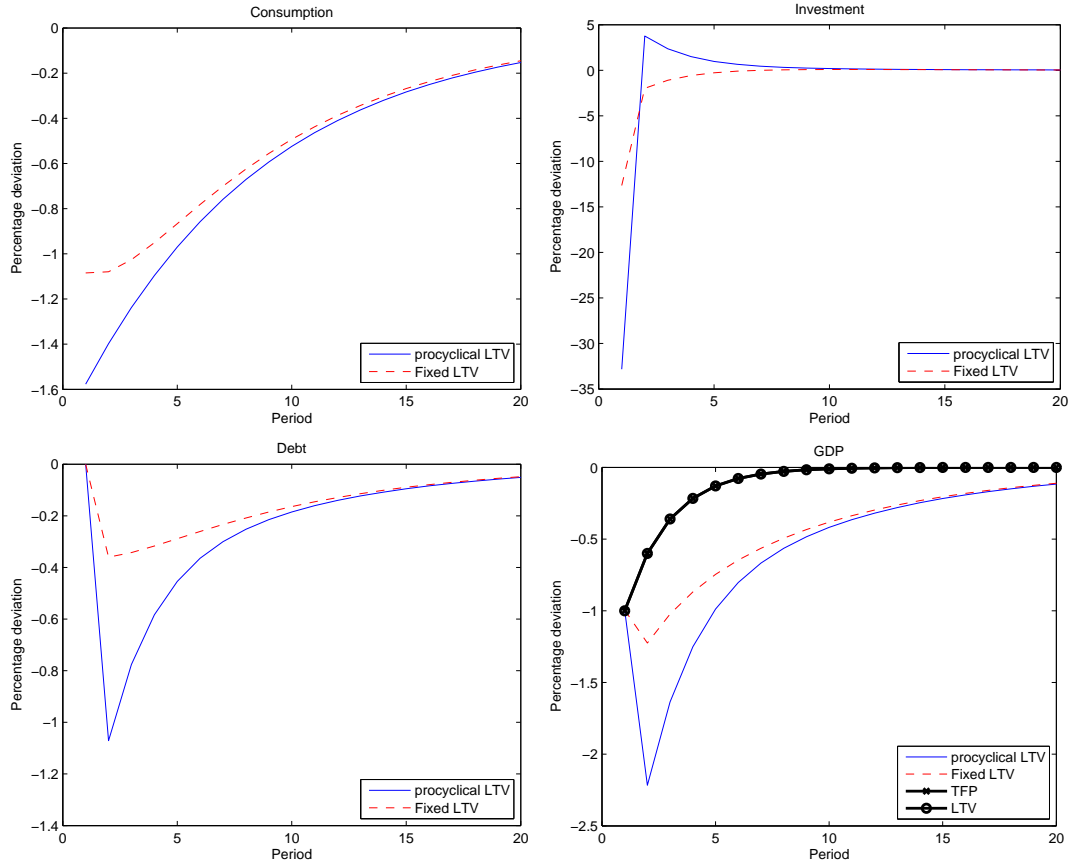
FIGURE 3.5: Impulse Responses, Procyclical Lending Standards.
The line labeled "Fixed LTV" corresponds to the responses to a 1% negative productivity shock, with φ_t constant at $\bar{\varphi} = 0.5$. The "procyclical LTV" corresponds to the responses to 1% negative shock to both TFP and the LTV ratio.

below its steady state level for exactly as long as productivity is below its long-run level.[19] Interestingly, when lending standards get tightened as productivity drops, the contraction in debt is almost three times bigger than when the LTV ratio is unchanged. Consequently, the drops in consumption and investment are much more accentuated under the procyclical LTV scenario: the decrease in investment on impact is between two and three times bigger under procyclical standards while that of consumption is about 50% bigger (-1.6% versus -1.1% under fixed LTV).

Figure 3.6 makes clear that the reaction of the risk premium and of asset prices is bigger under the procyclical LTV case. Aiyagari and Gertler (1999) showed that the presence of financial frictions entails an "overreaction" of asset prices to shocks to fundamentals. The results in Figure 3.6 show that frictions implying a procyclical behavior of the LTV ratio can further reinforce that overreaction.

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[19]As a robustness exercise, in Section 3.4.4 I report the results under iid shocks.

Indeed, the reaction of asset prices is almost twice as big under the procyclical LTV experiment than when the LTV ratio is constant. The procyclical behavior of lending standards can potentially have important consequences for the volatility of asset prices and real variables; I explore these implications in the next section.
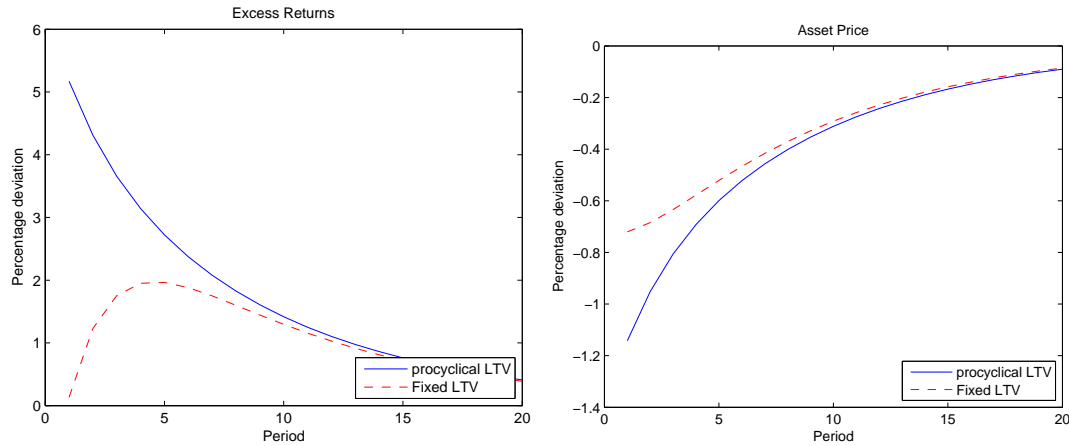

FIGURE 3.6: Amplified "Overreaction" of Asset Prices.
The line labeled "Fixed LTV" corresponds to the responses to a 1% negative productivity shock, with φ_t constant at $\bar{\varphi} = 0.5$. The "procyclical LTV" corresponds to the responses to 1% negative shock to both TFP and the LTV ratio.

3.4.3   Lending Standards and Macroeconomic Volatility

In this section I analyze the impact of reducing the degree of correlation of lending standards with the business cycle on the second moments of simulated macroeconomic aggregates. The reduction in correlation can be interpreted as the implementation of macro-prudential regulation aimed at reducing procyclicality in lending standards. The nature of the experiment in this section is the following. For each combination of the five values considered for $\rho_{(A,\varphi)}$ and $\bar{\varphi}$ I simulate 1000 samples of 100 periods, each with a burn-in of 500 periods, and I compute average unconditional moments across samples.

In Table 3.2 I report moments for a benchmark parametrization fixing $\bar{\varphi} = 0.5$ and considering values of $\rho_{(A,\varphi)} = \{0, 0.4, 0.8\}$. Although the model has no growth, the simulated series are filtered using the Hodrick-Prescott filter to focus the attention on the business cycle frequency.[20] The volatility of lending standards is 2.32% irrespectively of the value of $\rho_{(A,\varphi)}$, roughly between 1/3 and 1/2 of the volatility of

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[20]As a robustness check, Table 3.6 reports the results corresponding to unfiltered data.

TABLE 3.2: Simulation Results, HP Filtered Series.

Correlation TFP and LTV:	$\rho_{(A,\varphi)}$	0	0.4	0.8
a) Standard Deviations				
Lending Standards	$std(\varphi)$	2.32%	2.32%	2.32%
Output	$std(y)$	5.10%	5.68%	6.16%
Consumption	$std(c)$	3.07%	3.58%	4.01%
Investment	$std(i)$	106%	114%	122%
Asset Price	$std(q)$	2.35%	2.74%	3.06%
b) Cross-Correlations with Output				
Lending Standards	$corr(\varphi,y)$	0.25	0.36	0.45
Asset Price	$corr(q,y)$	0.47	0.55	0.60
Consumption	$corr(c,y)$	0.50	0.58	0.63
Trade balance to GDP	$corr(nx/y,y)$	0.38	0.31	0.26
c) Cross-Correlations with Asset Prices				
Lending Standards	$corr(\varphi,q)$	0.81	0.88	0.94
Consumption	$corr(c,q)$	0.99	0.99	0.99
Trade balance to GDP	$corr(nx/y,q)$	-0.44	-0.42	-0.41

Notes: All parameters as shown in Table 3.5. The long-run LTV ratio $\bar{\varphi}$ is 0.5. The series are filtered using the Hodrick-Prescott filter and a smoothing parameter equal to 100.

output. Although the correlation of innovations $\rho_{(A,\varphi)}$ ranges from 0 to 0.8, it is worth noting that the corresponding correlation of the LTV ratio with output goes only from 0.25 to 0.45. Fluctuations in φ_t have important effects in asset prices, as it was clear from the previous section. This is reflected in simulated series: The correlation of the LTV ratio with the asset price is 0.81 when $\rho_{(A,\varphi)} = 0$ and 0.94 when $\rho_{(A,\varphi)} = 0.8$.

What is the gain in terms of macro volatility from reducing $\rho_{(A,\varphi)}$ gradually from 0.8 to 0? Figure 3.7 and Figure 3.13 provide a visual summary of this experiment. Figure 3.7 presents the decrease in volatility for consumption, investment, output, foreign debt and net exports-to-GDP ratio, each relative to its own volatility when the correlation is 0.8, for a given long-run mean of the LTV ratio ($\bar{\varphi} = 0.5$, implying a leverage ratio of borrowers of 2). The figure shows potential sizeable gains in terms of volatility of macroeconomic aggregates from reducing the procyclicality of lending standards. In this sense, reducing the correlation of lending standards with productivity from 0.8 to 0 leads to a reduction in the volatility of

consumption of almost 1/4: the volatility of consumption under acyclical lending standards is about 25% lower than when $\rho_{(A,\varphi)} = 0.8$. The same exercise leads to a reduction in the volatility of output of around 17%. The biggest drop in volatility is achieved for the net export-to-GDP series, of around 30%. The gains in terms of macroeconomic volatility are significant, especially taking into account that reducing the correlation of the innovations from 0.8 to 0 implies a relatively modest reduction in the correlation between the LTV ratio and output, from 0.45 to 0.25 (see Table 3.2).[21] As a reference, removing the shocks to lending standards altogether reduces the standard deviation of consumption and output relative to the 0.8 correlation case by 53% and 36% respectively.
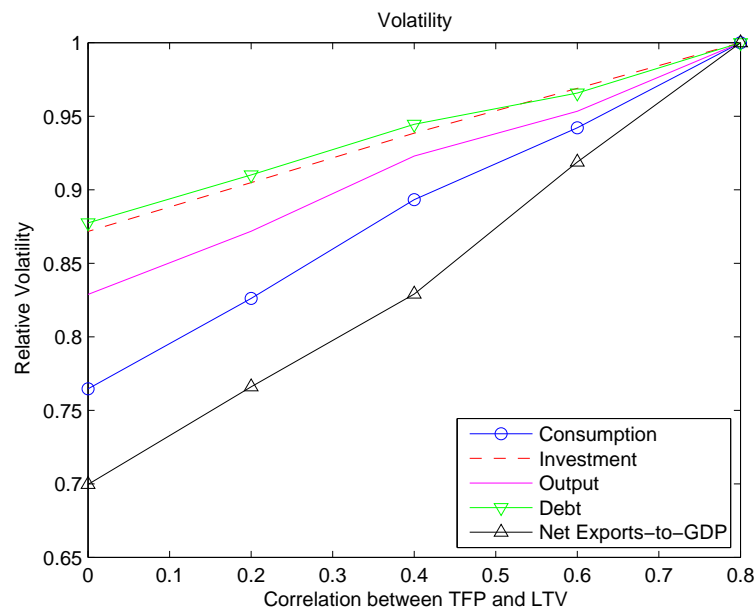

FIGURE 3.7: Stabilization Gains from Reducing Procyclicality of φ_t.
Each plot corresponds to the volatility of the series under different degrees of correlation ($\rho_{(A,\varphi)}$), relative to its own volatility when $\rho_{(A,\varphi)} = 0.8$. The long-run mean of the LTV ratio ($\bar{\varphi}$) is 0.5 in all cases. All series have been filtered using the Hodrick-Prescott filter.

Figure 3.13 reports the results for the same exercise but over a range of values for $\bar{\varphi}$. For each series the value on the vertical axis corresponds to its unconditional volatility relative to the one corresponding to $\rho_{(A,\varphi)} = 0.8$ and $\bar{\varphi} = 0.7$. The first thing to note is that, for all the variables, the volatility is higher the bigger the long-run leverage is. For example, the volatility of consumption is around 70% lower when the long-run leverage ratio is 1.4 ($\bar{\varphi} = 0.3$) than when it is 3.3

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[21]In the case of unfiltered series the correlation between the LTV ratio and output decreases from 0.65 to 0.45 when $\rho_{(A,\varphi)}$ is lowered from 0.8 to 0.

($\bar{\varphi} = 0.7$). Approximately the same ratio holds for output. In the case of asset prices, the unconditional volatility when ($\bar{\varphi} = 0.3$) is about half of the one under ($\bar{\varphi} = 0.7$). The most sensible variable in terms of unconditional volatility under different long-run leverage ratios is the trade balance: the volatility is several times higher when $\bar{\varphi}$ takes the maximum value.

The second result is that, for all the variables and for all long-run values of LTV ($\bar{\varphi}$), a reduction of the correlation $\rho_{(A,\varphi)}$ always entails a reduction in volatility. Whether the slope is steeper for different cuts over the $\bar{\varphi}$ dimension is hard to assess in the surface graphs. Figure 3.8 makes this comparison clearer for two variables: consumption and the trade balance to output ratio. The result is mixed: While for the case of consumption the gain in volatility from reducing the procyclicality of lending standards is roughly equivalent for different values of $\bar{\varphi}$, in the case of the trade balance the reduction is much more accentuated the higher the mean leverage of the economy.
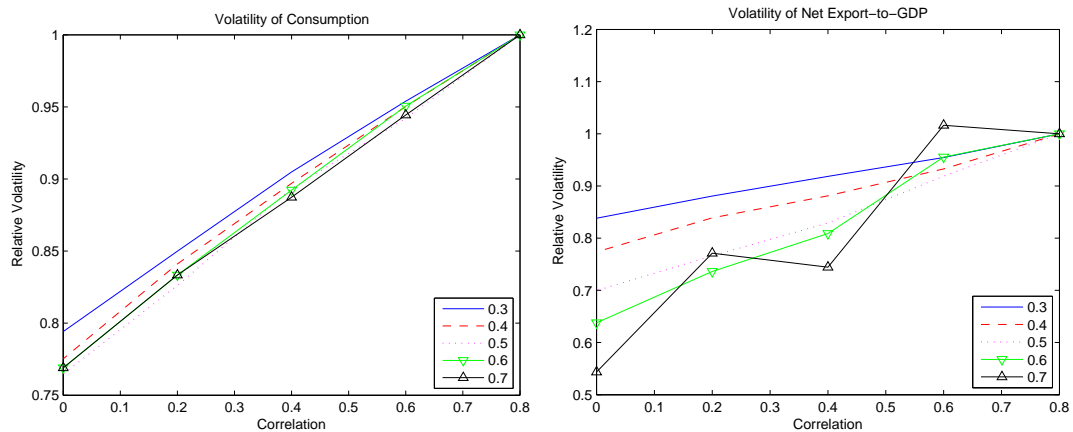

FIGURE 3.8: Stabilization Gains Under Different $\bar{\varphi}$ Values.
Each plot corresponds to the volatility of the series for a given long-run leverage ($\bar{\varphi}$) under different degrees of correlation ($\rho_{(A,\varphi)}$), relative to its own volatility when $\rho_{(A,\varphi)} = 0.8$. All series have been filtered using the Hodrick-Prescott filter.

Overall, the results in this section suggest that policies aimed at smoothing the procyclicality in lending standards can have seizable results in terms of volatility of macroeconomic aggregates. Although the model is highly stylized and abstracts from several elements that can be relevant for policy analysis, it can provide much of the insight into how the procyclical behavior of the financial frictions can affect macroeconomic volatility. Some caveats are of course in order. First, the simulations presented in this section are based on first order approximations of

the dynamic system under the conjecture that the collateral constraint is always binding. I do check that the Lagrange multiplier μ_t is always positive along the simulated paths. However, although a negative value of μ_t for some period would question the solution approach, a positive multiplier is not a proof that the collateral constraint has always been binding. A nonlinear approximation method would constitute a more robust alternative.[22] My guess though is that the presence of nonlinearities associated with occasionally binding constraints would, if any, amplify the effects of procyclical lending standards on macroeconomic volatility. Second, the model in this chapter abstracts completely from nominal issues, among which the presence of nominal frictions and of monetary policy, that might affect the transmission of financial shocks. Finally, the small open economy nature of the model implies that the real interest rate does not react to financial shocks that affect credit supply. Also, the model assumes that the financial friction affects the whole population in the economy. Exploring the quantitative implications of procyclical lending standards in a closed economy model with two groups of agents or in a two country model–where relative prices may also play a relevant role–are interesting avenues for future research.[23]

3.4.4   Persistence of Shocks and Business Cycles

In this section I repeat the numerical experiments under the alternative assumption of iid shocks, both for productivity and the LTV ratio. Figure 3.9 depicts the responses of the main macro-aggregates under both a fixed LTV ratio and procyclical lending standards when shocks to TFP and to the LTV ratio are iid instead of persistent as in the previous sections. Besides confirming the amplified overreaction of asset prices when φ_t behaves procyclically, the remarkable result in Figure 3.9 is the strong persistence of deviations from trend of asset prices despite the iid nature of the shocks. This persistent deviation of q_t gets reflected in the persistent responses of debt and consumption.

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[22]Although the model details differ, it is worth noting that some studies have found linear approximations relatively accurate in contexts similar to the one in this chapter. In a model using an asset in fixed supply as collateral, Iacoviello (2005) presents evidence suggesting that only for extreme parameterizations the accuracy of the linear approximation becomes questioned. Also Jermann and Quadrini (2009) solve a model with collateral constraints under both linear and nonlinear approximations and find that the solution based on a linear approximation is quite accurate. Nonetheless, the extent to which model details and parameter values might imply accuracy problems is an open question for future research.

[23]See Gruss and Sgherri (2009) for a model that introduces cycles in lending standards in a two-country two-good model, with endogenous fluctuations in the terms of trade.
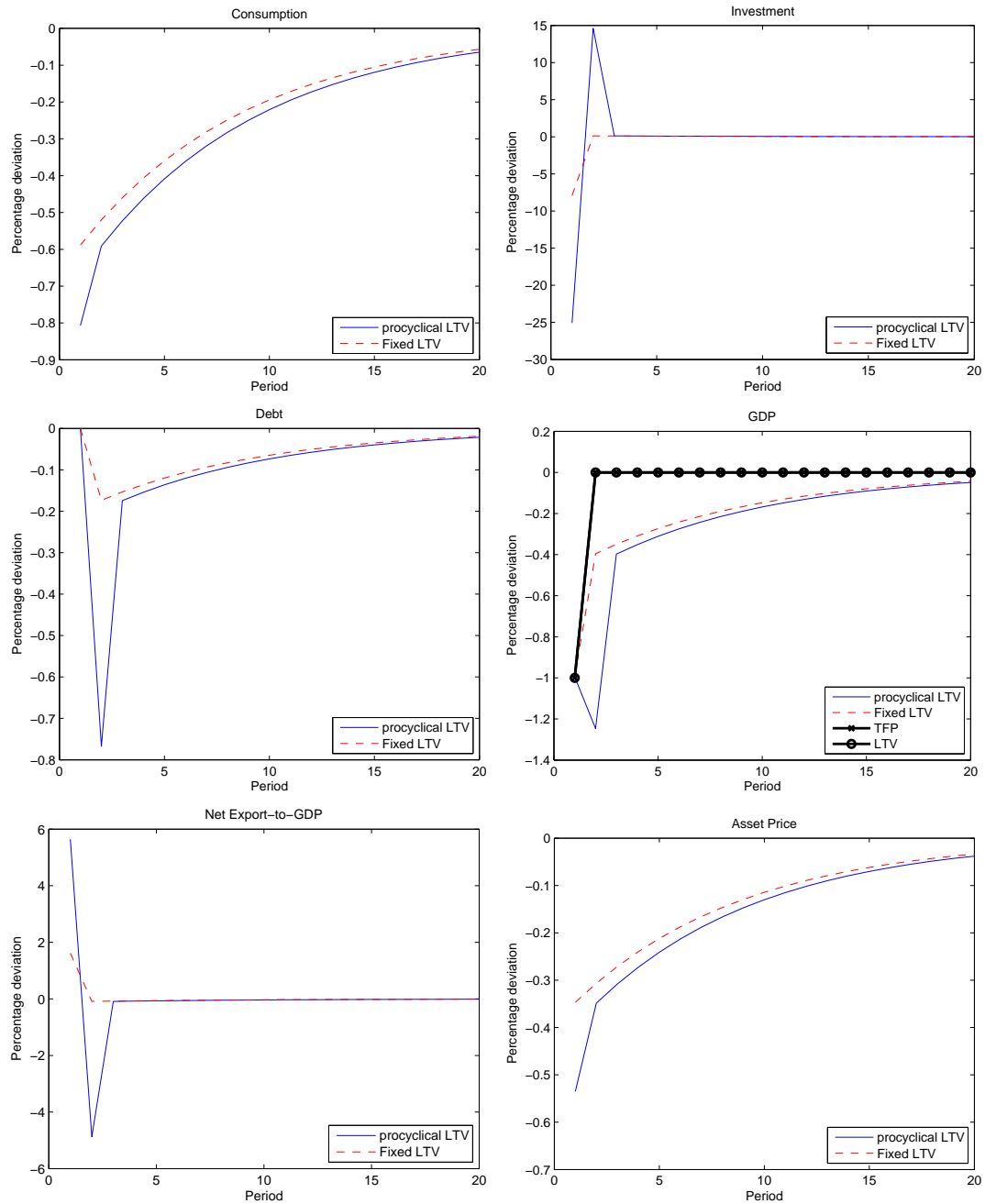
FIGURE 3.9: Impulse Responses, Procyclical Lending Standards, iid Shocks.
The line labeled "Fixed LTV" corresponds to the responses to a 1% negative productivity shock, with φ_t constant and equal to $\bar{\varphi}$. The "procyclical LTV" corresponds to the responses to 1% negative shock to both TFP and the LTV ratio.

Figure 3.10 shows the volatility results from simulations assuming iid shocks. The main results on volatility of reducing procyclicality of lending standards does not depend on the persistence of the shocks. In particular, the volatility of consumption, the only argument in the utility function of the representative agent, drops
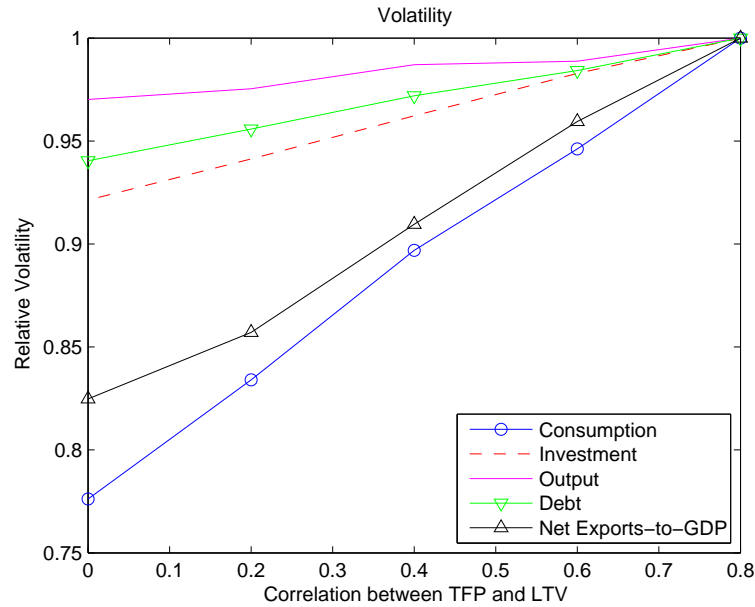
FIGURE 3.10: Stabilization Gains Assuming iid Shocks.

Each plot corresponds to the volatility of the series under different degrees of corre-
lation ($\rho_{(A,\varphi)}$), relative to its own volatility when $\rho_{(A,\varphi)} = 0.8$. The long-run mean
of the LTV ratio ($\bar{\varphi}$) is 0.5 in all cases. Shocks to TFP and to LTV ratio are iid.
All series have been filtered using the Hodrick-Prescott filter.

by almost $1/4$ when the correlation $\rho_{(A,\varphi)}$ is reduced from 0.8 to 0, similarly to
the result with persistent shocks. The main difference between the exercise with
persistent shocks refers to the volatility of output: with iid shocks the volatility
of GDP gets reduced much less than when shocks are persistent.

TABLE 3.3: Persistence of Business Cycles

Procyclicality of Lending Standards ($\rho_{(A,\varphi)}$)	0	0.2	0.4	0.6	0.8
Autocorrelation of Output	0.16	0.25	0.32	0.39	0.44

Credit constraints have been signaled as a key mechanism transforming shocks
into persistent movements in output (e.g. Kocherlakota 2000). This model con-
firms this result. The first column in Table 3.3 reports the autocorrelation of
output when shocks to TFP and to φ_t are iid and $\rho_{(A,\varphi)} = 0$, fixing $\bar{\varphi} = 0.5$. Even
if shocks are iid, output displays positive autocorrelation (0.16). Interestingly,
however, procyclicality in lending standards implies higher persistence of business

cycles relative to the shocks hitting the economy: When the simulations are repeated for positive $\rho_{(A,\varphi)}$ under iid shocks, the autocorrelation of output increases substantially. Indeed, when $\rho_{(A,\varphi)} = 0.8$ the autocorrelation of output is 0.44, three times higher than when $\rho_{(A,\varphi)} = 0$.[24] In sum, the procyclicality of lending standards also introduces a significant source of persistence of output.

3.4.5 An Endogenous Function for Lending Standards

Fully endogenizing the procyclical behavior of lending standards in a DSGE model is beyond the scope of this chapter.[25] However, in this section and as a robustness exercise I replace the stochastic process for φ_t in Equation 3.3 postulating an endogenous functions that links lending standards with the cyclical stance of the economy. Adrian and Shin (2010) suggest that financial intermediaries adjust their balance sheets to changes is asset prices in a way that implies an aggregate increase/reduction in credit supply. There is evidence suggesting that this behavior entails relaxation/tightening in lending standards (see Bayoumi and Melander 2008 for example). Motivated by this evidence I assume an ad-hoc functional form for φ_t that links lending standards to the cyclical stance of asset prices in the economy. More precisely, I postulate:

$$\varphi_t = \frac{\exp\left(a(q_t - \bar{q}) + b\right)}{1 + \exp\left(a(q_t - \bar{q}) + b\right)} , \tag{3.12}$$

where b is a parameter determining the LTV ratio in the non-stochastic steady state and a determines the sensibility of φ_t to deviations of q_t from its steady state value.[26] Figure 3.11 shows the response of the LTV ratio to a negative 1% productivity shock for $a = 0$ and $a > 0$. The parameter b was set to 0 such that the long-run LTV ratio is 0.5, the intermediate value in the exercises in the previous sections. In the procyclical lending standards case, the parameter a was set to 160 so that the unconditional standard deviation of the LTV ratio is similar than under the specification of lending standards in Equation 3.3 used in the previous sections. With these parameter values, a 1% negative TFP shock leads to a drop of $\hat{\varphi}_t$ on impact of around 2.5% (see Figure 3.11).

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[24]These results correspond to unfiltered series. The same result holds for HP filtered series.

[25]Fostel and Geanakoplos (2008) model the tightening of margins explicitly, but in a finite-horizon model with limited rationality.

[26]Under the specification of φ_t in Equation 3.12, its long-run level is $\bar{\varphi} = \frac{\exp(b)}{1+\exp(b)}$.
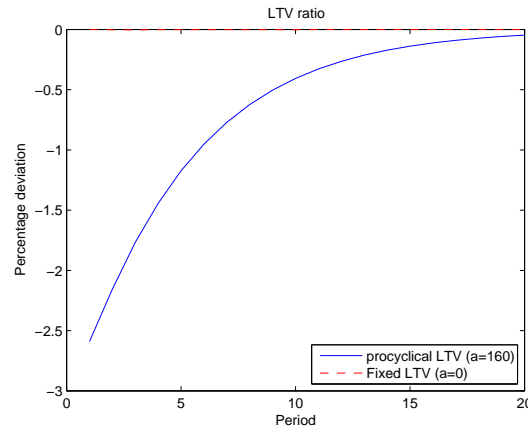
FIGURE 3.11: Response of LTV Ratio in Equation 3.12 to a -1% TFP Shock.

Figure 3.12 shows the response of consumption, investment, debt, output, excess returns and asset prices to a negative productivity shock assuming alternatively $a = 0$ (i.e. a fixed LTV ratio) and $a > 0$ (procyclical lending standards). When lending standards get eased as asset prices are above trend and tightened when they are below trend, the responses of all the variables are much more accentuated than when the LTV ratio is a constant. The last two graphs show the amplified "overreaction" of asset prices due to procyclical lending standards: Excess returns rise on impact by 15% above their steady state level when $a = 160$. Instead, when $a = 0$ they only rise gradually, reaching a maximum deviation from trend of around 2% five periods after the shock. The asset price drops to only 0.7% below its steady state level when $a = 0$ while it decreases almost 3% when lending standards are procyclical. Due to the higher drop in the value of the collateral under procyclical lending standards, $\hat{d}_t$ drops by five times more than when the LTV is fixed. Consequently, the drops in consumption and in investment in response to a negative productivity shock is much more pronounced when the LTV ratio behaves procyclically: the drop in consumption is more than 3 times bigger and, in the case of investment, the decrease is around 7 times bigger. The latter gets reflected in the much higher drop in output under procyclical lending standards: $\hat{y}_t$ reaches a bottom of -1.2% when the LTV is fixed but of almost -4.5% when the LTV ratio behaves procyclically.

Table 3.4 reports the second moments of simulated macroeconomic aggregates assuming alternatively $a = 0$ and $a = 160$. When $a = 0$ the LTV ratio is a constant; when $a = 160$ the LTV ratio reacts to deviations of asset prices from trend and its standard deviation is 2.44%. The volatility of q_t is more than 3.5

times higher when lending standards are assumed to be procyclical. In the case of consumption this ratio is 3 times and for investment it is more than 6 times. The standard deviation of output is 7.64% when $a = 160$ but it is only 2.23% when the LTV ratio is fixed.
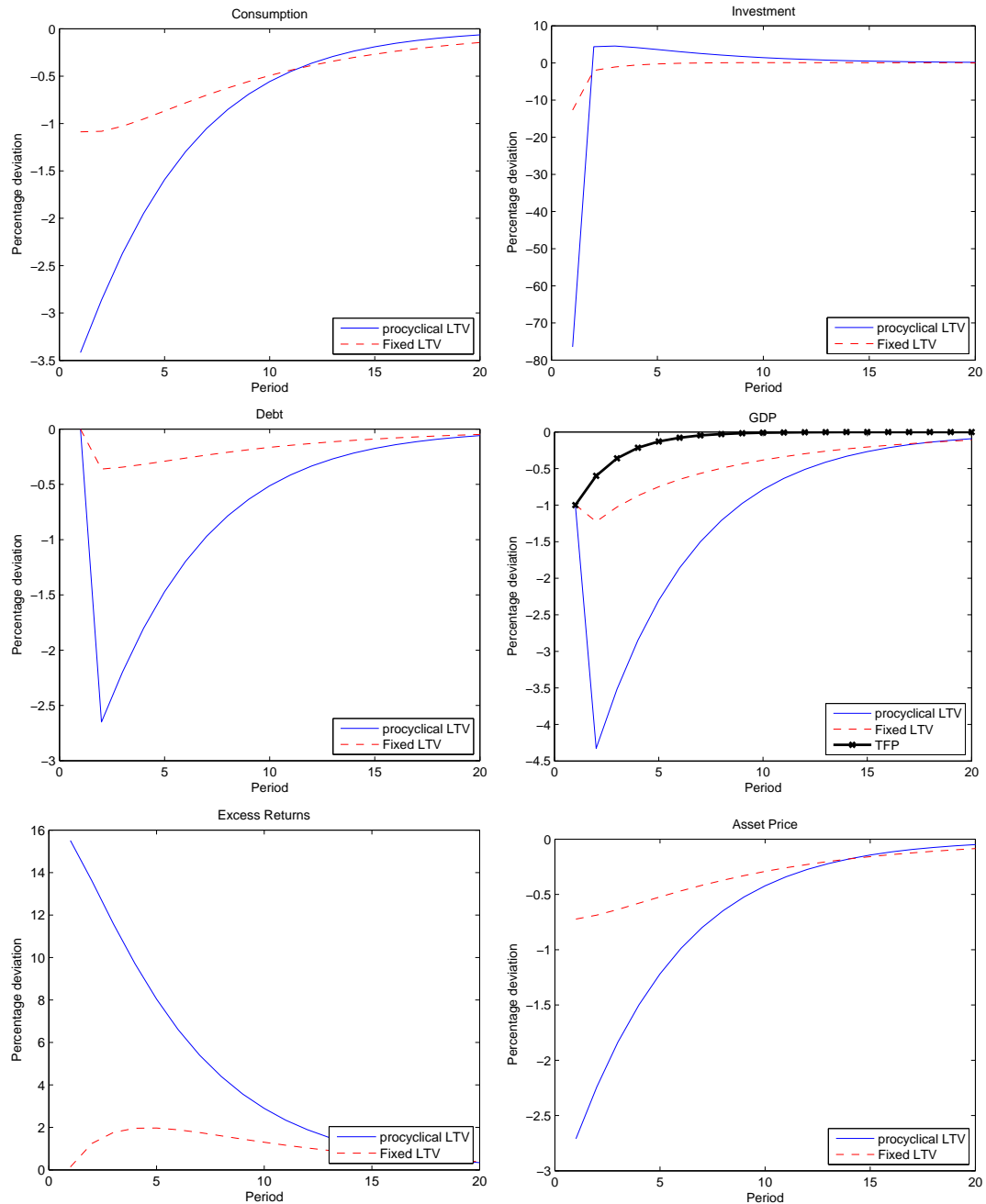

FIGURE 3.12: Alternative Specification for Lending Standards in Equation 3.12.
The line labeled "Fixed LTV" corresponds to the responses to a 1% negative productivity shock, with φ_t as in Equation 3.12 with $a = 0$ while the "procyclical LTV" responses correspond to the case with $a > 0$.

TABLE 3.4: Simulation Results, LTV Ratio in Equation 3.12.

Standard Deviations	a:	0	160
Lending Standards	$std(\varphi)$	0%	2.44%
Output	$std(y)$	2.23%	7.64%
Consumption	$std(c)$	2.11%	6.38%
Investment	$std(i)$	22.7%	145.1%
Asset Price	$std(q)$	1.37%	5.05%

Notes: a takes 2 alternative values: 0 (fixed LTV) and 160 (procyclical LTV); $b = 0$; the other parameter values are as in Table 3.5. The series are filtered using the Hodrick-Prescott filter and a smoothing parameter equal to 100.

3.5   Concluding Remarks

Recent contributions in the empirical literature suggest the existence of financing frictions in the relationship between financial intermediaries and their creditors, introducing a credit supply channel that amplifies business cycle fluctuations. Indeed, several studies show that, consistently with the extended use of risk-measures like Value-at-Risk, leveraged financial institutions manage actively their balance sheets in response to changes in the price of assets they hold and in measured risk in the economy, and that this behavior affects in turn the tightness of credit standards, the volume of aggregate credit, asset prices and real activity. Although the role of non-financial borrowers' "creditworthiness" in amplifying or generating cycles in macro models has been amply studied in the literature, the presence of frictions in the funding side of financial intermediaries has been much less explored. This chapter develops a small open economy model that, while keeping financial intermediaries as a veil, incorporates the dynamics of their balance sheets documented in the empirical literature in a reduced form. Agents in the domestic economy trade a non-contingent bond with the rest of the world and face an endogenous collateral constraint where the maximum leverage ratio varies with the business cycle, mimicking the procyclical behavior of lending standards. What I am trying to explore, in a simple way, is the macroeconomic effect of financial intermediaries easing/tightening credit standards along the cycle, for some reason not modeled explicitly but consistently with the empirical evidence.

Despite the highly stylized nature of the model, it predicts reactions of the risk premium, asset prices and macroeconomic activity to innovations in productivity

or to financial shocks consistent with the empirical evidence documented for instance in Adrian *et al.* (2010b). The tightening of lending standards leads to a sharp increase in the risk premium and a drop in asset prices. The drop in the market value of the collateral decreases the possibility of rolling over debt and forces agents to cut spending in consumption and investment, the latter leading to a drop in output after one period. When I consider shifts in the loan-to-value ratio that are correlated with the business cycle, I find that the "overreaction" of asset prices documented in Aiyagari and Gertler (1999) gets further amplified and this leads to a bigger reaction of real variables. In my quantitative experiments the response of asset prices is twice as big when lending standards get tightened as productivity drops than when the loan-to-value ratio is constant. Also the drop in output is around twice as big, while for the case of consumption the drop is 50% bigger under a procyclical reaction of lending standards.

Regarding the destabilizing effect of procyclicality in lending standards mentioned in the literature, my simulations suggest that introducing some "macro-prudential" regulation to reduce the degree of correlation of credit standards with the cycle can lead to sizable gains in terms of macroeconomic volatility. In this sense, in my model reducing the correlation of the loan-to-value ratio with output from 0.45 to 0.25 is associated with a reduction in the volatility of real consumption of approximately one fourth. The procyclical behavior of lending standards is also found to contribute significantly to the persistence of business cycles relative to the shocks. Although the model is highly stylized, it contributes to the policy debate on macro-prudential regulation by exploring what can be the stabilizing effects of implementing policies aimed at lowering the degree of procyclicality in lending standards.

Assessing the quantitative implications of extending the model to include more realistic features represents a potential avenue for future research. The parsimonious nature of the model in this chapter helped to focus on the main aspects of the propagation mechanism. However, a richer model might be needed to explore policy instruments and to evaluate the potential benefit of concrete policies targeting the procyclicality of credit standards. Modeling explicitly financial intermediaries to endogenize the procyclical behavior of lending standards is of course another interesting direction for future research.

3.6   Appendix Chapter 3

3.6.1   Other Tables and Figures

<div align="center">TABLE 3.5: Model Parametrization</div>

| a) Preferences and Technology	Symbol	Value
Discount factor	β	0.92
Capital income share	α	0.5
Capital depreciation parameter	δ	0.1
Unconditional mean of TFP	$\bar{A}$	0.61
Persistence of TFP shock	ρ_A	0.6
Standard deviation of TFP shock	σ_A	0.02
b) Credit Standards		
b.1) Stochastic Specification (Equation 3.4)		
Average LTV ratio	$\bar{\varphi}$	$\{.3, .4, .5, .6, .7\}$
Persistence of LTV shock	ρ_φ	0.6
Standard deviation of LTV shock	σ_φ	0.05
Correlation of A_t and φ_t shock innovations	$\rho_{(A,\varphi)}$	$\{0, .2, .4, .6, .8\}$
b.2) Endogenous Function (Equation 3.12)		
Average LTV ratio	$\exp(b)/(1+\exp(b))$	.5
LTV function parameter	a	160
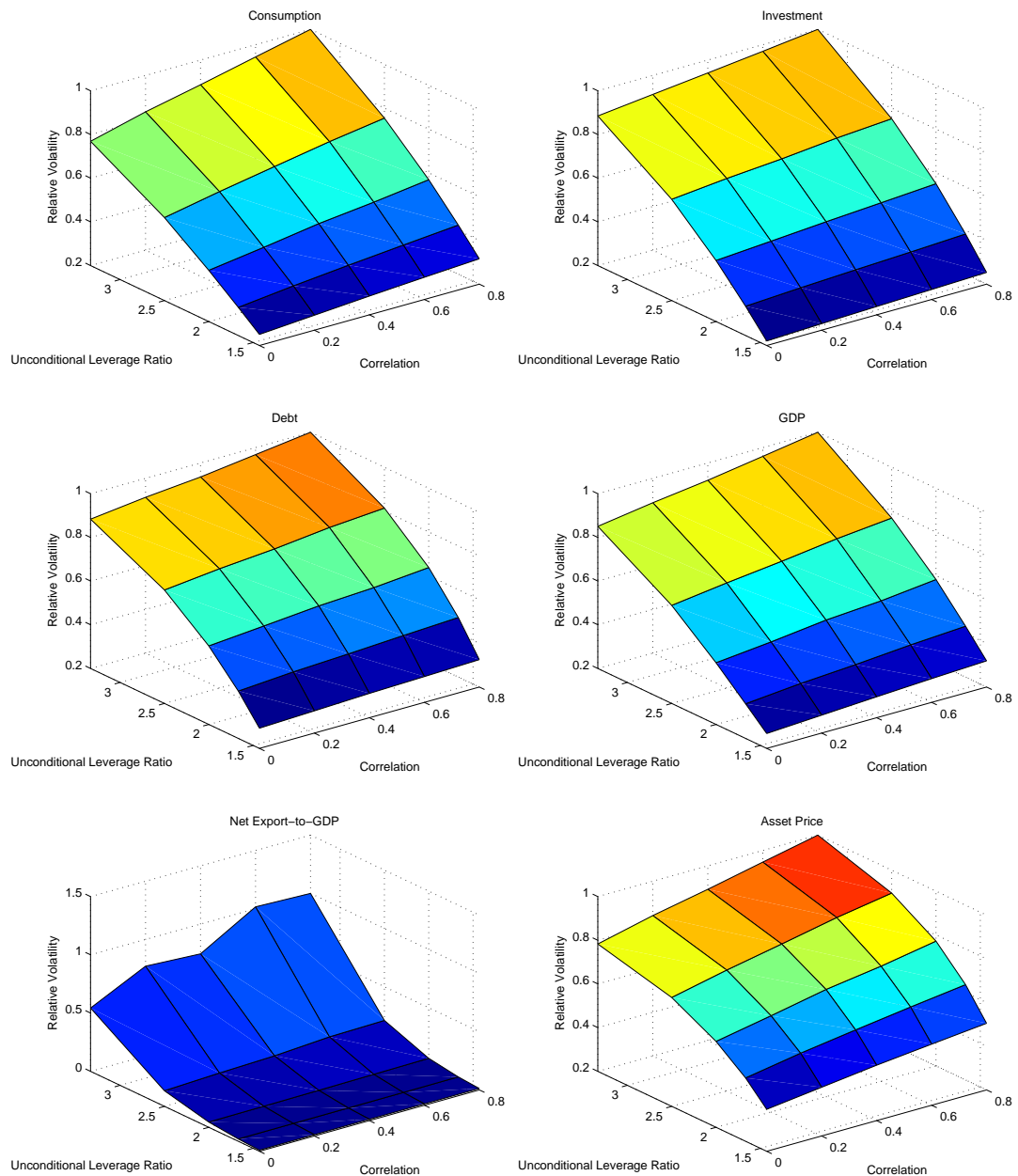
FIGURE 3.13: Stabilization Gains from Reducing Procyclicality of φ_t.
Each plot reports the volatility of the series under different degrees of correlation $(\rho_{(A,\varphi)})$ and long-run LTV ratio $(\bar{\varphi})$, relative to its own volatility when $\rho_{(A,\varphi)} = 0.8$ and $\bar{\varphi} = 0.7$. All series have been filtered using the Hodrick-Prescott filter.
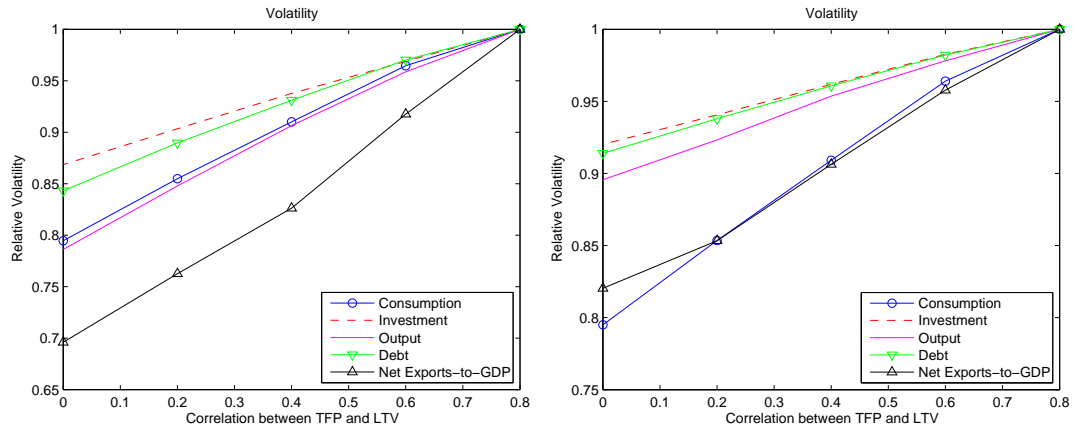
FIGURE 3.14: Stabilization Gains from Reducing Procyclicality of φ_t, Unfiltered Series, Persistent and iid Shocks.

Each plot corresponds to the volatility of the series under different degrees of correlation ($\rho_{(A,\varphi)}$), relative to its own volatility when $\rho_{(A,\varphi)} = 0.8$. The long-run mean of the LTV ratio ($\bar{\varphi}$) is 0.5 in all cases. The series are unfiltered. The *left panel* corresponds to persistent shocks ($\rho_A = \rho_\varphi = 0.6$) while the *right panel* corresponds to iid shocks.

TABLE 3.6: Simulation Results, Unfiltered Series.

Correlation TFP and LTV:	$\rho_{(A,\varphi)}$	0	0.4	0.8
a) Standard Deviations				
Lending Standards	$std(\varphi)$	3.05%	3.05%	3.05%
Output	$std(y)$	7.84%	9.04%	9.98%
Consumption	$std(c)$	6.00%	6.87%	7.55%
Investment	$std(i)$	110%	119%	127%
Asset Price	$std(q)$	4.13%	4.78%	5.29%
b) Cross-Correlations with Output				
Lending Standards	$corr(\varphi, y)$	0.45	0.56	0.65
Asset Price	$corr(q, y)$	0.76	0.81	0.84
Consumption	$corr(c, y)$	0.76	0.82	0.85
Trade balance to GDP	$corr(nx/y, y)$	0.22	0.17	0.14
c) Cross-Correlations with Asset Prices				
Lending Standards	$corr(\varphi, q)$	0.64	0.76	0.86
Consumption	$corr(c, q)$	0.99	0.99	0.99
Trade balance to GDP	$corr(nx/y, q)$	−0.28	−0.26	−0.25

Notes: All parameters as shown in Table 3.5. The series are unfiltered.

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