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Macro-Financial Challenges in Emerging Markets

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Abstract

This dissertation thesis consists of three essays on macroeconomics and finance. In these essays, I focus on events which adversely affect emerging markets and present challenges to economic policy and central bank thinking. My aim is to contribute to the existing empirical literature by providing new evidence on the role of private credit, effects of macroprudential policies and understanding of the exchange-rate pass-through.

The first essay evaluates policy measures taken to curb bank credit growth in the private sector in the pre-crisis period 2003–2007. The analysis is based on an original survey conducted on central banks in Central and Eastern Europe. The findings reveal substantial policy intervention and indicate that certain measures - particularly asset classification and provisioning rules; and loan eligibility criteria - might have been effective in taming bank credit growth.

The second essay contributes to the existing literature on early warning indicators as well as to the discussion on the appropriateness of credit-to-GDP gap as a leading variable for any country for activation of the countercyclical capital buffer instrument in Basel III. We exploit long-run credit series for 36 emerging markets and evaluate their quality to signal a crisis by using receiver operating characteristics (ROC) curve and area under the curve (AUC). The results show that nominal credit growth and the change in credit-to-GDP ratio have the best signaling properties and significantly outperform the credit-to-GDP gap in almost all specifications for policy-relevant longer horizons in EMEs.

The third essays studies how exchange rate pass-through to inflation has changed since the global financial crisis. The main findings can be summarized as follows: First, exchange rate pass-through in emerging economies decreased after the financial crisis, while exchange rate pass-through in advanced economies has remained relatively low and stable over time. Second, the declining pass-through in emerging markets is related to declining inflation. Third, the findings highlight the importance to control for non-linearities when estimating exchange rate pass-through.

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Acronyms

AE Advanced Economies

AUC Area Under the Curve

BCBS Basel Committee on Banking Supervision

BIS Bank for International Settlements

CEE Central and Eastern Europe

CCB Countercyclical Capital Buffer

CPI Consumer Price Index

DSR Debt-Service Ratio

DTI Debt-To-Income Ratio

ECB European Central Bank

EU European Union

EME Emerging Market Economies

ERPT Exchange Rate Pass-Through

EWI Early Warning Indicator

FX Foreign Exchange

GMM Generalized Method of Moments

GDP Gross Domestic Product

HP Hodrick-Prescott

IMF International Monetary Fund

LR Long-Run

LTI Loan-To-Income Ratio

LTV Loan-To-Value Ratio

MRR Marginal Reserve Requirements

NEER Nominal Effective Exchange Rate

NPL Non-Performing Loans

Q Quarter

ROC Receiver Operating Characteristics

RR Reserve Requirements

SRR Special Reserve Requirements

TPR True-Positives Ratio

FPR False-Positives Ratio

WTI West Texas Intermediate

Chapter 1

Introduction

The recent financial crisis sparked new interest in understanding the link between macroeconomy and finance. The new body of theoretical and empirical literature explores the role of private credit, macroeconomic frictions and financial crises (Brunnermeier & Sannikov (2016), Di Maggio & Kermani (forthcoming), Gertler & Karadi (2015), Gertler & Kiyotaki (2015), Jordà *et al.* (2013), Jordà *et al.* (2015), Korinek & Simsek (2016), Mendicino *et al.* (2016), Mian & Sufi (2011), Mian *et al.* (forthcoming), Reinhart & Rogoff (2009)).

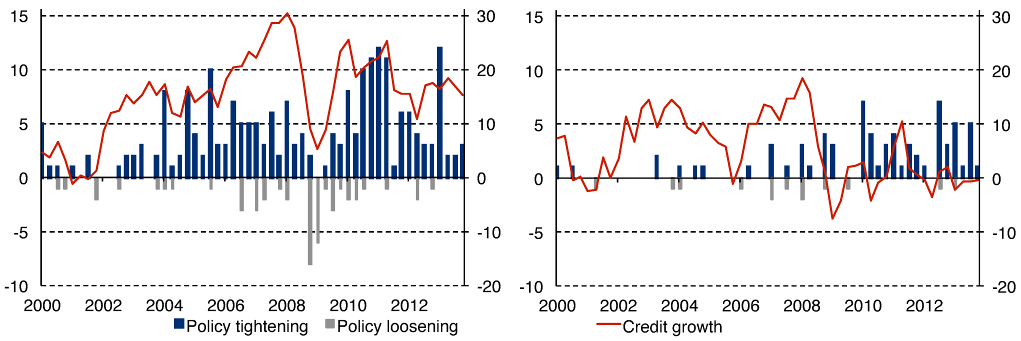
This dissertation thesis presents three essays on macro-financial challenges in the emerging markets. The thesis focuses on the challenges to economic policy and central bank thinking at the crossroads of macroeconomics and finance. All three essays are empirical in nature and they aim to address topics at the frontier of current policy discussion. These selected topics cover an assessment of effectiveness of central banks' policies to curb credit booms, early warning indicators to signal banking crises and an analysis of shifting patterns in exchange rate pass-through to inflation. The essays have been collated over the full course of my PhD studies which also included two practical experiences in international institutions – European Central Bank and Bank for International Settlements – and two research stays at universities abroad – Waseda University (Japan) and Princeton University (USA). These essays are co-authored and I assess my contribution to be 75%, 75% and 50%, respectively.

My research interest narrows down to the environment of emerging market economies (EMEs). EMEs are important global economic players and the world economy has become increasingly reliant on their development. EMEs currently create 40% of the world GDP and they contribute to approximately 80% of the world growth.[1]

Business cycles in emerging markets, unlike developed markets, are characterized by dramatic reversals in fiscal and monetary policies, large volatilities and dramatic current account reversals, the so-called "sudden stop" phenomenon. Aguiar & Gopinath (2007) show that shocks to trend growth – rather than transitory fluctuations around a stable trend– are the primary source of fluctuations in emerging markets.

EMEs also experienced more pronounced credit dynamics than advanced economies (Figure 1.1). On one hand, revivals of credit are seen as a sign of healthy banking system and confidence in the economy. On the other hand, excessive credit growth increases imbalances and amplifies vulnerabilities in the economy. Most recently, Mian *et al.* (forthcoming) document a systematic empirical negative relation between household debt and business cycles across 30 countries from 1960 to 2012. The authors also show stronger negative relation for countries with less flexible exchange rate regimes – a common feature of EMEs. In this dissertation, we begin by examining private credit more closely (Essay 1 and 2). In Essay 3, we proceed to investigate the role of sensitivity of exchange rate movements on inflation.

Figure 1.1: Private credit and macroprudential policies: 2000–2013



(a) Emerging markets (b) Advanced economies

LHS: Frequency of macroprudential policy tightening (loosening) is marked in positive (negative) scale. RHS: Year-on-year credit growth to the non-financial private sector.
Source: Akinci & Olmstead-Rumsey (2015), IMF Global Macroprudential Policy Instruments and BIS.

[1]China alone currently contributes to approximately one third of the world GDP growth, while the remaining EMEs contribute to an additional 45%.

EMEs also serve as good laboratories for policy experiments. For instance, EMEs were the forerunners of macroprudential polices (Figure 1.1). The emerging world introduced measures of a macroprudential nature a full decade before the term "macroprudential" became a consensus across policymakers and academics.[2]

In the first essay (Chapter 2), we start by focusing on the policy measures designed to cope with the credit boom in emerging Europe in the period 2003–2007. This essay contributes to the literature in the field of effectiveness of macroprudential policies (Vandenbussche *et al.* (2015), Cerutti *et al.* (2015), Claessens *et al.* (2013), Crowe *et al.* (2011), Kuttner & Shim (2013)) in two ways.

First, we present an original dataset on all relevant policy measures applied across the region over the period 2003–2007 to slow private credit growth. The dataset is not based on any aggregate database but was created in collaboration with all eleven central banks in the CEE region. Thanks to the direct survey, we exclusively consider responses that the central banks categorized as "measures to cope with the credit growth". In total, we record 82 policy interventions which were implemented over five years in eleven CEE countries. The survey covers a wide range of instruments from monetary, administrative to macroprudential policies. We believe that the description of such a dataset is a valuable input to understand the role of both private credit and guide the policy response.

Second, our findings indicate that some policy measures, such as LTV limits, DTI limits or assets classification and provisioning rules, could have played a role in slowing down credit expansion. These results remain robust to different methodologies. We also find that a long-term effect of the policy actions was hindered by new circumvention channels such as direct cross-border lending from parent institutions or non-bank lending channel. This phenomenon has been recently emphasized by Cizel *et al.* (2016), who provide a new evidence of substitution effects towards non-bank credit upon introduction of bank-oriented policy measures.

In the second essay (Chapter 3), we pay attention to the role of credit in early warning models. Since the financial crisis, significant efforts have also been attributed to the development of early warning models (Alessi *et al.*

[2]Loan-to-value ratio (LTV) and debt-to-income ratio (DTI) limits implemented in Hong Kong and Korea in early 2000s are one of the first mentions of successes in the field of macroprudential policies (Cassidy & Hallissey (2016), Crowe *et al.* (2011), Kim *et al.* (2014), Igan & Kang (2011), Wong *et al.* (2011)).

(2015), Babecký *et al.* (2014), Drehmann *et al.* (2010), Drehmann & Juselius (2014), Behn *et al.* (2013)). The work has mostly focused on advanced economies and it finds a robust evidence that credit-to-GDP gap (the deviation of the credit-to-GDP ratio from the long-term trend) is the single best performing indicator to signal future banking crises.

These findings directly contributed to the design of a counter-cyclical capital buffer (CCB). CCB is a new macroprudential instrument introduced by the Basel III regulation to make banks more resilient to banking crises. Basel III requires banks to set aside more capital when credit expansion is strong and use it in the times of distress. Credit-to-GDP gap has become a reference guide to activate the CCB.

Main caveats of this approach emphasized potential weaknesses of the statistical technique behind the construction of the gap indicator (Edge & Meisenzahl (2011), Geršl & Seidler (2010), Jakubík & Moinescu (2015) and ECB (2011)), such as the reliability on end-of-sample estimates and quality of the information of the time series for converging countries undergoing financial deepening. These concerns are particularly relevant for emerging markets, which are currently designing their macroprudential policy frameworks and are looking for variables with reliable signaling properties to anchor their policy decision-making process.

This essay aims to fill the gap in the literature by focusing explicitly on emerging markets. Our objective is to investigate whether the strong signaling properties of credit-to-GDP gap hold robustly also for EMEs as they can suffer from shorter data availability, financial deepening or any other weaknesses of the technique behind the construction of the gap. We build upon an ample emprical evidence that credit booms create risks to future macroeconomic performance (Reinhart & Rogoff (2009), Schularick & Taylor (2012), Jordà *et al.* (2013), Jordà *et al.* (2015), Baron & Xiong (2016)). As a result, we center my attention on the signaling properties of a range credit-based variables.

We analyzed the performance of six alternative credit-based variables in signaling banking distress in the context of emerging markets, both for bank and total credit. Our results show that nominal credit growth and the change in credit-to-GDP ratio have the best signaling properties and significantly outperform the credit-to-GDP gap in almost all specifications for policy-relevant longer horizons.

In the third essay (Chapter 4), we zoom into the post-crisis period to document new challenges to the exchange rate channel of monetary policy. Recent changes in exchange rate pass-through (ERPT) to consumer prices have reappeared at the center of central bank thinking such as the research of Bank of England (Forbes (2014) and Forbes (2015)) and Bank for International Settlements (BIS). Together with the co-authors from the BIS, Richhild Moessner and Előd Takáts, we document a large decline of exchange rate pass-through to consumer price index inflation since the global financial crisis.

To the best of our knowledge, this is the first work that explores this new shift in the ERPT trend. The results are consistent with the implications of the menu cost theory of price setting: when inflation is higher, exchange rate changes are passed through more quickly and to a larger extent because firms have to adjust prices frequently anyway.

The essay also provides strong empirical evidence for a causal link between lower inflation and lower pass-through in emerging market data, in line with Calvo & Reinhart (2002) and Choudhri & Hakura (2006). The results can also be seen as extending the analysis of the low inflation - low pass-through link from advanced economies in the 1990s of Takhtamanova (2010) to emerging markets in the 2000s. The pattern of declining pass-through in EMEs holds similarly for contemporaneous (quarterly), yearly and long-run pass-through estimates. The findings are stable to different methodologies, global controls, time windows and exchange rate measures.

Policy lessons

This dissertation aims to address the core of the policy-relevant research for emerging economies. In this section, I would like to address key findings and take stock of the discussed policies. How do these findings matter for current and future policy making?

Private credit and banking crises: Relevance of the private credit has been emphasized both by academics (Jordà *et al.* (2013), Mian *et al.* (forthcoming)) and policymakers (Brockmeijer *et al.* (2011), CGFS (2012), IMF-FSB-BIS (2016)). In essay 2, we find that credit-based variables tend to have good early warning qualities in signaling future banking crises. However, one size does not fit all. Unlike the results reported from advanced economies (Drehmann & Juselius 2014), for EMEs credit-to-GDP gap suffers from weaknesses (Geršl & Seidler (2015) or Edge & Meisenzahl (2011)). Namely, limited data availability or dramatic reversals in credit cycles can lead to spurious results and produce unreliable credit-to-GDP trends which are essential for the construction of the gap measure. Instead, we show that EME policymakers can do sufficiently well by relying on simpler metrics such as credit growth and the change in credit to GDP.

Macroprudential policy and its leakages: In essay 1, we analyze the effectiveness of central banks' policies to combat credit booms. The main findings highlight the role of macroprudential measures (e.g. limits on LTV / LTI, provisioning rules...). Since the crisis, macroprudential measures became a part of standard policy toolbox of central banks (CGFS (2016), ESRB (2014)). Macroprudential policy can be designed in a more targeted manner as compared to broad monetary policy. On the other hand, one of the main lessons from CEE experience, as discussed in essay 1, is that the effectiveness was mitigated by newly emerged circumvention channels (similar evidence is also reported by Cizel *et al.* (2016) and Houston *et al.* (2012)).

Looking forward, policymakers may choose to close documented loopholes in their future policy design. For instance, cross-border leakages created by the lending by the branches of foreign banks or foreign parent banks directly can be addressed by required reciprocation. Cross-sector leakages from shadow banking activities can be limited through broader definition of macroprudential policies. For instance, activity-based measures (in contrast to institution-based measured) set limits on total borrower's exposure to the risk regardless whether the debt burden comes from banks or non-banks. These practices are becoming part of the new design of debt-service-to-income (DSTI) limits. This aim can be further reinforced by relying on more granular data (credit registries and lending surveys can be an example). More research shall also be done in terms of understanding sensitivity of impact on actual calibrations.

Foreign currency: In essay 1, we document that the countries hit the hardest by the crisis had a large proportion of foreign currency (FX) denominated loans. Sudden exchange rate fluctuation lead to significant wealth shocks to unhedged households (i.e. Hungary). Additionally , high share of FX loans limited the effectiveness of conventional policy tools.

Exchange rate interventions tends to be a common instrument for EMEs to correct external imbalances. This is valid even more so for highly indebted economies. A shift in currency composition of private loans towards foreign currencies increases the imbalances further and in times of crises forces policymakers to rethink the use of policy actions.

Moreover, as we show in essay 3, the role foreign currency channel of monetary policy is also diminishing. On the positive side, high values of ERPT are often a feature of periods of macroeconomic instability rather than periods of stability (Ben Cheikh & Rault 2015). Yet, the lower pass-through in emerging markets also implies that the exchange rate channel of monetary policy might be less effective to affect inflation than before the financial crisis.

Lower levels of ERPT today suggest that central banks in general should have less "fear of floating", at least from an inflation perspective. Our results also reinforce the importance of price stability by showing that lower inflation also reduces pass-through. In fact, there might be a positive feedback loop: lower pass-through could in turn further contribute to price stability. As a consequence, EMEs might benefit from maintaining credible and transparent monetary policy.

Chapter 2

Measures to tame credit growth: Are they effective?

This chapter focuses on policy measures taken to curb bank credit growth in the private sector in the pre-crisis period 2003–2007. Our analysis is based on an original survey conducted in 2010 on eleven central banks in Central and Eastern Europe (CEE). The findings reveal substantial policy intervention: a total of 82 measures were implemented in CEE during the period considered. The essay presents a panel data analysis of the effectiveness of the policy measures adopted in the region. The overall results indicate that certain measures - particularly asset classification and provisioning rules and loan eligibility criteria - might have been effective in taming bank credit growth, especially if applied in the context of more general policy measures featuring a combination of various instruments. However, in countries in which the authorities managed to somewhat decrease the flows of bank credit into the economy, the measures were often circumvented via direct, cross-border credit from foreign banks and credit provided by domestic, non-bank financial companies.

The paper was co-authored with Adam Geršl and published in Economic Systems (2014, 38, pp. 7–25). We would like to thank the representatives of the central banks that participated in the survey for providing the data. Special thanks are due to Tomislav Ridzak and participants of the 2012 IES Economic Meeting, Prague, September 21, 2012, for their helpful comments. The findings, interpretations and conclusions expressed in this paper are entirely those of the authors and do not necessarily represent the views of any of the abovementioned institutions. This work was supported by the Grant Agency of Charles University (project GA UK No. 564612) and the Grant Agency of the Czech Republic (project GA CR No. 403/10/1235).

2.1 Introduction

Credit growth is an inherently beneficial process. Its revival is often seen as a sign of a healthy banking system and confidence in the economy. In case of emerging markets, credit growth is also associated with financial deepening. For illustration, in 2003, none of the economies in Central and Eastern Europe (CEE)[1] exceeded a 50% private credit to GDP threshold (figures range from 13.7% in Romania to 49.2% in Croatia). Despite these initially low levels, credit development in the 2003–2007 period underwent turbulent changes that affected the borrowing of both households and firms. In CEE, credit growth was also associated with catching up to the advanced economies. During the 2003–2007 period, private credit growth in CEE on average increased three times more rapidly than in the euro area, reaching its highest pace in mid-2006.

Despite the benefits of financial deepening, excessive credit growth increases imbalances and can amplify the vulnerabilities of a financial system. Credit development over the period 2003–2007 raised concerns among both policymakers and academics that it was excessive, unsustainable and potentially creating over-heating pressures on the economy (Backé *et al.* (2007), Duenwald *et al.* (2005), Enoch & Ötker-Robe (2007), Kraft & Jankov (2005), Popa (2007), Zumer *et al.* (2009)). As a result, a number of countries attempted to either inhibit these credit booms or limit specific aspects of the credit expansion that posed risks to the system, such as foreign currency denominated loans.

This essay tracks the experiences of eleven CEE economies in their credit development transition (2003–2007). In particular, it closely examines the policy measures introduced by central banks to alleviate the adverse effects of credit growth.

The key contribution of this essay is twofold. First, we present a detailed dataset on all relevant policy measures applied across the region over the period 2003–2007 to slow private credit growth. The dataset is not based on any aggregate database but was created in collaboration with all eleven CEE central banks. Thanks to the direct survey, we exclusively consider responses that the central banks categorized as "measures to cope with the credit growth". In total, we record 82 policy interventions which where implemented over five years in eleven CEE countries. The survey covers a wide range of instruments from monetary, administrative to macroprudential policies. We believe that

[1] Bulgaria, the Czech Republic, Croatia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.

the description of such a dataset is a valuable input for a better understanding the development of both private credit and the guiding the policy response.

Second, our aim is to contribute to the discussion on effectiveness of central bank conventional and unconventional policies by providing evidence from the CEE region. We assess the policy effectiveness by combining our survey results with aggregate macroeconomic data (private credit, GDP, lending rate and exchange rate volatility) in a dynamic panel data estimation. The main analysis in performed on generalized method of moments (GMM) using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator but the results stay robust under within group estimators.

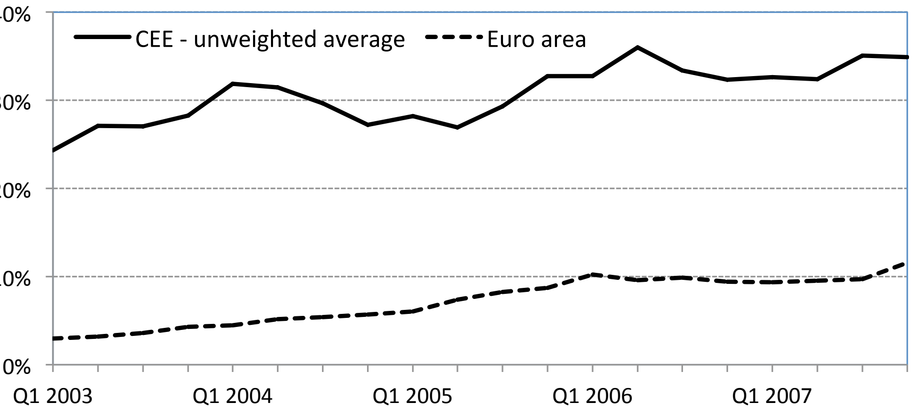
Our findings suggest that certain instruments, primarily asset classification and provisioning rules and LTV/LTI limits, might have been effective in taming bank credit growth, especially if applied in the context of a more general policy that featured a combination of various instruments. However, none of the policy tools seem to perform well over longer periods. In countries in which the authorities managed to somewhat decrease the flows of bank credit into the economy, the measures were often circumvented via direct, cross-border credit from foreign banks and credit provided by domestic, non-bank financial companies. These findings are in line with the results on strong cross-sector substitution effects recently documented by Cizel *et al.* (2016).

This essay was originally influenced by Hilbers *et al.* (2005), which, in addition to analyzing the theoretical and practical advantages and disadvantages of each policy instrument, also presented a complete dataset of policy measures implemented by a broad group of Central and Eastern European countries prior to mid-2005. In this spirit, our work collects data throughout the most vibrant period of policy interventions until end-2008. Furthermore, the essay also contributes to the emerging stream of literature on the effectiveness of macroprudential policies, notably Vandenbussche *et al.* (2015), Dell'Ariccia *et al.* (2012) and Lim *et al.* (2011), who provide econometric evidence of the effectiveness of various tools in CEE countries.

The remainder of the essay is structured as follows: Section 2.2 introduces stylized facts regarding credit development in CEE and a literature review. Section 2.3 examines the menu of policy measures policymakers may implement to counter a credit boom in greater detail. Section 2.4 presents the results of a survey of central banks in the CEE region and discusses the most popular measures. Section 2.5 discusses the panel data analysis. Section 2.6 assesses the effectiveness of the measures. Finally, Section 2.7 concludes.

2.2 Stylized facts and literature review

Figure 2.1: Private credit growth 2003–2007: CEE vs. euro area



Source: ECB, IFS IMF, autors' calculation

The ratios of private credit to GDP in CEE countries were low in 2003 compared to those in the euro area, but over the 2003–2007 period, bank credit extended to the private sector rose more rapidly than in the euro area, reaching its highest pace in mid-2006 (Figure 2.1). By 2007, some CEE countries (such as the Baltics or Slovenia) reached levels comparable to those in certain euro area countries (Figure 2.2).

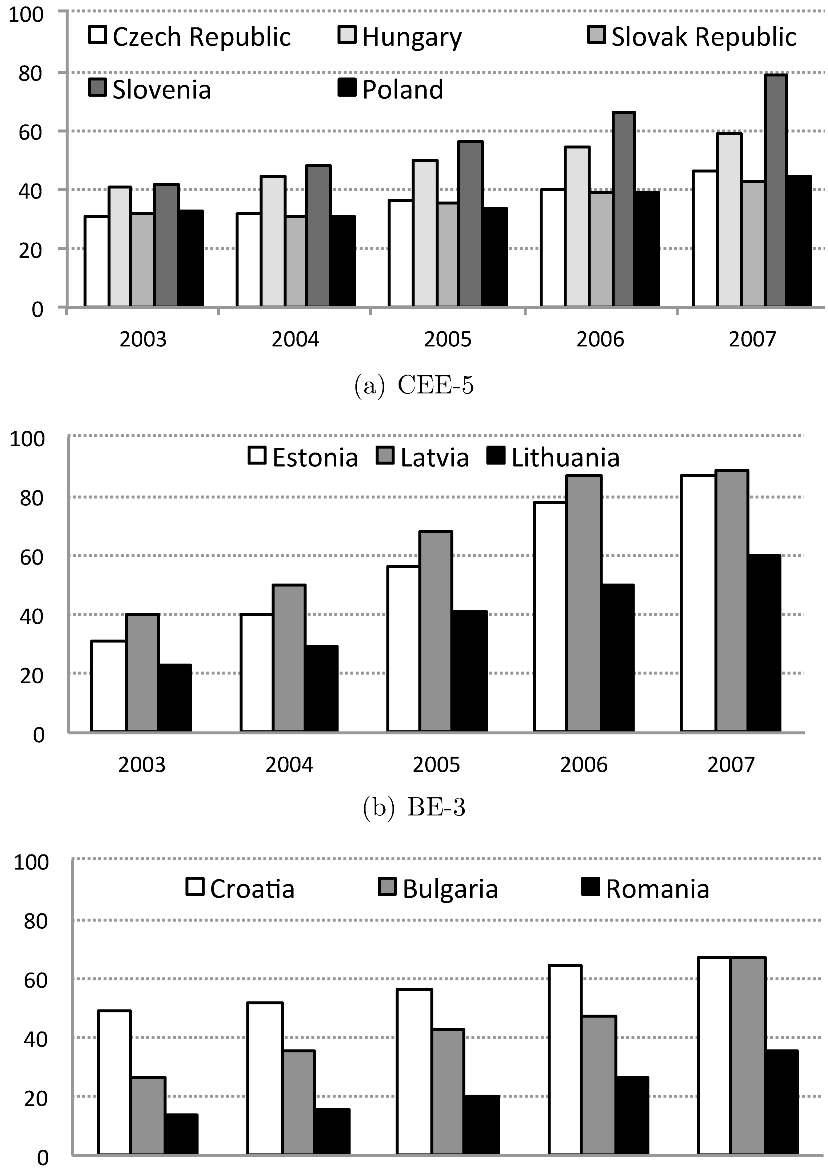
In most countries, foreign-currency denominated (FX) loans were a significant component of credit growth. While the amounts of FX loans vary substantially, the phenomenon of FX lending to unhedged borrowers (such as households without foreign-currency income) was widespread and appeared in all CEE economies except the Czech Republic and Slovakia (Figure 2.3).[2]

Foreign ownership of banks is a characteristic of all CEE countries except Slovenia. This attribute is a result of the privatization of formerly state-owned banks to foreign owners, primarily Western European banking groups, and direct "greenfield" entries of foreign banks (Geršl (2007), Frait *et al.* (2011)). In a number of CEE, banking systems with high foreign ownership - but not all of them (i.e., not in the Czech Republic, Slovakia or Poland) - foreign banks also provided funding for their subsidiaries to finance local credit growth. In addition, foreign banks also play an important role in providing direct cross-border

[2]The decrease in the share of FX loans in Slovenia, Slovakia and Estonia over the period 2007–2010 is due to the adoption of the euro.

credit, typically to large corporations in CEE countries. Such direct, cross-border lending often substantially limits the effectiveness of domestic policy measures to dampen credit dynamics, as at least some share of local credit could eventually be reallocated to the foreign parent companies' books.

Figure 2.2: Private credit to GDP (2003–2007)



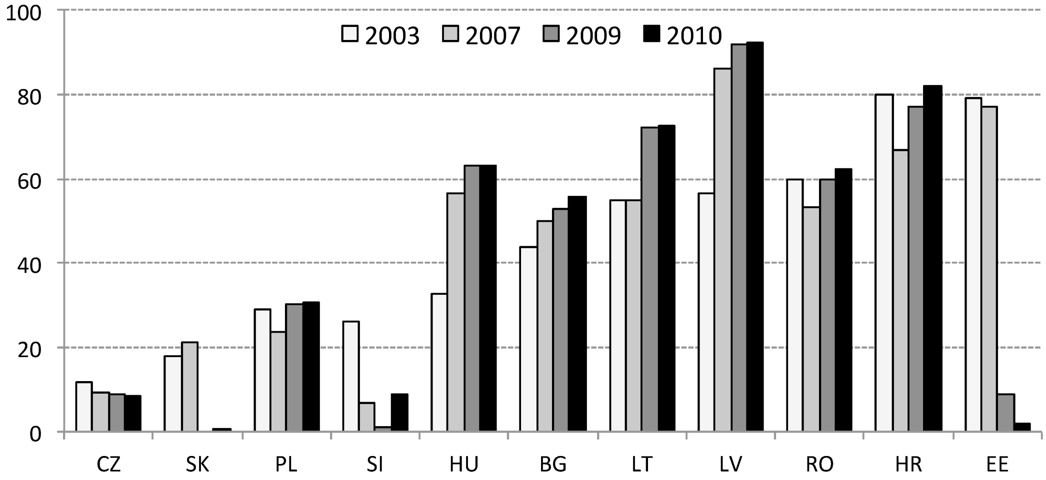
(a) CEE-5

(b) BE-3

(c) SE-3

Source: EBRD (2009)

Figure 2.3: Foreign currency loans (% of total loans to the private sector)



Source: Zumer *et al.* (2009) and national central banks

As a reaction to the financial turmoil in the last quarter of 2008, credit growth suddenly ceased. The downturn also reflected country- and region-specific factors. The slowdown in credit growth occurred in conjunction with the global development. Economies in which credit growth was funded by capital inflows were hit the hardest. Foreign parent banks, confronted with liquidity and capital shortages, came under severe liquidity pressure and were forced to halt new lending or even deleverage in CEE countries (Bakker & Klingen 2012). Country- and region-specific factors also contributed to the slowdown, such as domestic and regional imbalances, followed by a collapse in domestic demand and corrections in housing markets (Zumer *et al.* 2009). Given the excessive FX-denominated borrowing, credit developments were adversely affected by exchange rate depreciation (where applicable under the exchange rate framework and the existence of FX lending).

Before the crisis, literature mostly focused on understanding the credit dynamics and identification of excessive credit growth. The most wide-spread approach to address this issue was to derive the long-term equilibrium level of credit with respect to selected macroeconomic fundamentals (Boissay *et al.* (2007), Brzoza-Brzezina (2005), Égert *et al.* (2006), Bakker & Klingen (2012), Zumer *et al.* (2009), Geršl & Seidler (2012)). The majority of the studies identified a few CEE economies with excessive credit development during the period 2003–2007 that could have adversely affected financial stability.

A parallel stream of literature focused on the measures implemented by policymakers to tame credit growth. Hilbers *et al.* (2005) identify the primary risks associated with credit booms and discuss the advantages and disadvantages of each of the policy instruments (macroeconomic, prudential, regulatory and administrative)which were implemented to counter and reduce these risks. The authors draw lessons from the experience of a wider group of economies from the Central and Eastern European region, up to mid-2005. Our work aims to both complement and extends previous findings for the period until end-2007.

The question of the effectiveness of specific policy measures was also approached on a country basis: Kraft & Jankov (2005), Galac (2010) and Kraft & Galac (2011) for Croatia; by Popa (2007) for Romania; or as a part of the financial stability report analysis published by the National bank of Poland (2007) or Latvijas Banka (2007).

The financial crisis led to a more intense debate over the role of macroprudential policy, its tools, implementation challenges and effectiveness.[3] As CEE provides a rich pool of experience from the credit boom period, the policy measures previously applied in the region were labeled macroprudential and were subject to further analysis. Dell'Ariccia *et al.* (2012), who explore past credit booms in a large sample of economies, find little evidence that the macroprudential measures implemented in the region had a lasting impact on the boom itself. However, Dell'Ariccia *et al.* (2012) suggest that the measures could have been successful in terms of addressing specific features of credit growth (such as currency denomination) or building capital and liquidity buffers against future downturns.

Lim *et al.* (2011) investigate the effectiveness of macroprudential policies for 49 countries, including CEE. The authors employ three different approaches to assess the effectiveness: (i) case studies on small groups of countries, (ii) a simple approach examining the performance of relevant variables before and after the intervention and (iii) panel regression analysis to assess the effectiveness of the measures with respect to various variables. Their findings identify the conditions under which the measures can be successfully implemented and potential challenges. In particular, Lim *et al.* (2011) stress the necessity of a sound regulatory framework, high-quality supervision, coordinated policy ac-

[3]For example, at the international level, the IMF initiated four strands of work (i) identifying indicators of systemic risk, (ii) reviewing country experiences regarding the use and effectiveness of macroprudential policy, (iii) assessing the effectiveness of different institutional frameworks for macroprudential policy and (iv) assessing the multilateral aspects of macroprudential policy (Brockmeijer *et al.* 2011).

tions and the role of instruments in different phases of the business and credit cycle.

Vandenbussche *et al.* (2015) focus on the prudential measures employed in CEE countries to limit credit growth, but interestingly assess their effectiveness in terms of their impact on house price inflation. Their contribution also lies in coding the prudential measures with respect to their strength, rather than using the binary coding scheme of whether an instrument was applied that has been used in other studies. Vandenbussche *et al.* (2015) model housing price dynamics using an error correction model. They find that capital measures and non-standard liquidity measures had an impact on housing price inflation.

2.3 Measures to tame credit growth

Reviewing the 2003–2007 period, the prevailing consensus on credit development seemed to favor a "benign" view as opposed to an active policy involvement. The justifications were twofold. First, it is difficult to identify excessive credit expansion that is not in line with macroeconomic fundamentals, especially in emerging markets. Second, any measure entails costs and distortions. Moreover, not all credit booms are followed by financial crises or poor macroeconomic performance. Duenwald *et al.* (2005) estimate the likelihood of a banking crisis following a lending boom to be 20%. Based on IMF (2004), 70% of credit booms coincide with either an investment or consumption boom in the emerging market. As a result, the implementation of policy measures is a challenging task, as is an ex ante evaluation thereof.

Even after deciding to act, the task does not become any simpler, as additional questions emerge. What policy tools do policymakers actually have at their disposal? How strong are they? What are their limitations? Crowe *et al.* (2011) stress there is "no silver bullet" among the policy options available. Each policy introduces costs and distortions, and its effectiveness is limited by loopholes and implementation problems. Broad measures (e.g., monetary policy rates) are more difficult to circumvent, and hence potentially more effective, but they typically involve greater costs. Conversely, more targeted measures (e.g., the application of specific macroprudential tools) may limit costs but are hampered by loopholes that jeopardize their effectiveness (Crowe *et al.* 2011). Clearly, one must also account for interactions among the range of tools, their complementariness and potential conflicts. Finally, every economy is unique, with distinctive characteristics and institutions that significantly influence the feasibility of each measure and generate potential trade-offs.

In line with Hilbers *et al.* (2005), we use the following categorization of policy measures to counter excessive credit growth: (i) monetary policy measures, (ii) macroprudential and supervisory measures, and (iii) administrative and other measures.[4] However, we acknowledge that any categorization is to some extent arbitrary. For example, we categorize reserve requirements as a monetary policy measure, while a number of countries would treat them as a macroprudential measure. Moreover, some capital controls (categorized as administrative measures) are actually constructed as unremunerated reserve requirements on a specific type of funding and, in a broader sense, could thus be considered monetary policy measures.

2.3.1 Monetary policy measures

Increasing key policy rates (interest rate response) makes borrowing more expensive and reduces the demand for loans. However, interest rate increases pose numerous concerns. As interest rates affect an entire economy, they will only be used to address macroeconomic overheating pressures. Therefore, they are rarely employed to tame a credit boom as such. Furthermore, interest rate tightening may pose additional concerns, such as the exchange rate framework, excessive FX borrowing or already high capital inflows.

Changes in reserve requirements (RR) are a powerful instrument widely employed in CEE during the transition period. Enoch & Ötker-Robe (2007) stress that an increase in RR can be essential in the one-off sterilization of excess liquidity or in accommodating structural changes in the demand for reserves. In addition to changes in the required level, measures often also include reserve requirements differentiated by currency, type of deposit or broadening the reserve base.

However, RR changes have numerous limitations, as they hinder financial intermediation (i.e., RR are perceived as a tax on financial intermediation, as they are not remunerated or only at a rate that is considerably below the market level). Potential negative outcomes include reduced financial deepening,

[4]Fiscal measures are also an important element of the policy mix. As this essay predominantly works with the measures introduced by central banks, we did not focus on the collection of a broad range of fiscal policies. With that being said, some fiscal measures - such as changes in taxes intended to tame credit growth - feature in the dataset but are part of a group (iii): administrative and other measures.

bank off-shoring or, in the case of subsidiaries, increased direct, cross-border loans from parent banks, banks accepting more risky projects, discrimination of banks vis-à-vis non-banks, etc.

2.3.2 Macroprudential and supervisory measures

Macroprudential and supervisory measures are primarily intended to buttress the banking sector against risks that are usually accumulated during periods of strong credit growth and may materialize thereafter. Therefore, even if they fail to halt the boom, they may nonetheless help to cope with the crunch. Yet, even if dampening a credit boom is not regarded as a primary objective, authorities often hope that macroprudential and supervisory measures have the potential to decrease the supply of credit to some extent due to increased credit provision costs (e.g., higher capital or provisioning requirements for new loans, etc.). Crowe *et al.* (2011) find that when a policy succeeded in slowing a boom and avoiding a systemic crisis, it nearly always involved some prudential measures.

Selecting appropriate measures is also subject to the nature of the risk associated with credit growth. Macroprudential and supervisory measures are suitable means of eliminating inconsistencies or distortions in the market (e.g., excessive loan concentration or unhedged FX positions). Otherwise, these measures should be designed such that they support macroeconomic policies, i.e., they should be part of a comprehensive package of measures rather than a separate tool. Hilbers *et al.* (2005) emphasize that the effects of prudential policies are limited in the absence of prudent fiscal policy or if monetary and fiscal regimes persistently create incentives that encourage credit growth. As a result, macroprudential measures were typically employed in conjunction with other instruments. Unlike monetary policy, macroprudential measures have narrower and more targeted goals, which result in reduced costs. However, as these instruments are narrower in scope, they are easier to circumvent, which encourages regulatory arbitrage and risk shifting.

Successful implementation of macroprudential and supervisory measures relies on a wide range of requirements. In detail, these are adequate enforcement capacity on the part of regulatory authorities, cross-border supervisory cooperation (and in the case of foreign-owned banks, adequate scrutiny from supervisors in their home countries) and coordination between the supervisors of bank and non-bank financial institutions. Unless a common dialog and collaborative measures are achieved, isolated attempts to curb excessive bank credit growth may not only prove unsuccessful but also may also create new loopholes in the system and introduce further obstacles.

2.3.3 Administrative and other measures

Administrative (direct) measures are explicitly designed to limit credit growth, either via direct limits on credit provided or via a given funding source (controls on capital inflows, reserve requirements on bank borrowing from abroad, differentiated reserve requirements on domestic and foreign currency deposits, etc.). Direct tools are strong inhibitors of credit growth. While they entail substantial costs and distortions, their effect is often only temporary. Nonetheless, in numerous cases these tools were implemented in the CEE region over the period studied.

In this group, we also consider fiscal measures, primarily those related to changes in taxes. As credit expansion is often closely related to a real estate boom, the fiscal authority can increase real estate transaction taxes and property taxes and cut various fiscal and quasi-fiscal incentives that may encourage certain types of lending (such as subsidies or guarantees for housing loans, interest rate deductions from the tax base, etc.).

2.4 Survey results

The core data were collected via a direct survey of central banks in the CEE region in 2010. Central banks were asked to provide information regarding the measures they used to tame credit growth over the 2003–2008 period. The tools were categorized into three main groups, as explained in the previous chapter: (i) monetary policy measures, (ii) macroprudential and supervisory measures, and (iii) administrative and other measures. The central banks also specified the date (month and year) when such steps were taken. We managed to collect responses from all eleven central banks (response rate=100%).[5,6]

[5] The Bank of Slovenia only provided Yes/No responses regarding the use of policy tools without stating the dates of implementation. As Slovenia does not fall into the category of countries that employed such policy measures extensively, its responses are nonetheless valuable.

[6] The Czech National Bank indicated in their survey response that no specific policy actions were taken to directly address the private credit dynamics. As a result, the reported "CZ" column remains empty. Our final results are compiled both including the Czech Republic (in the main text) and excluding it (in the Appendix C).

Table 2.1: Survey results: Policy responses used in CEE (2003–2008)

Measures	**CZ**	**SK**	**LT**	**LV**	**EE**	**HU**	**PL**	**RU**	**BG**	**HR**	**SI**
Monetary measures											
Interest rate response				x			x	x			
Reserve requirements				x	x			x	x	x	
- Changes in the required level				x	x			x	x	x	
- Differentiated by currency								x			
- Differentiated by type of deposit				x							
- Broaden the reserve base				x				x			
Prudential and Supervisory measures											
Capital requirements or risk weights			x	x	x	x	x	x	x	x	
Liquid asset requirements		x					x			x	
Tighter asset classification rules								x	x		
Tighter provisioning rules				x				x	x		
Tighter eligibility criteria for certain loans				x		x		x			
- Limit on LTV				x				x			
- Limit on LTI / payment to income								x			
Tighter rules on valuation criteria											x
Measures targeted on FX borrowing			x	x			x	x		x	
- Targeting unhedged borrowers				x			x	x		x	
- Tighter net open position limits			x	x							
Soft measures - non-binding for banks		x	x	x	x	x	x		x	x	x
Tighter supervision				x		x		x	x		
Administrative and other measures											
Capital controls			x								
Credit ceilings								x	x	x	
Taxes on real estate transactions				x							
Average YoY credit growth	15.6%	14.0%	47.9%	49.5%	33.6%	20.5%	13.8%	55.0%	42.4%	18.4%	23.9%

Table 2.1 illustrates the overall list of measures used in the region. The CEE experience is very rich; every measure included in the survey was implemented at least in one of the countries. Overall, we observed 82 policy interventions over the period. However, the country experiences varied significantly.

First, most of the countries that were identified as experiencing rapid credit booms resorted to a more active policy involvement. For detailed results, see Boissay *et al.* (2007), Brzoza-Brzezina (2005), Égert *et al.* (2006),Backé *et al.* (2007), Zumer *et al.* (2009) and Geršl & Seidler (2012), who also document the correlation between the use of various tools and credit growth. In Table 2.1 we also report average credit growth over the period. The correlation between the credit growth and the intensity of policy actions for our sample is positive (with correlation coefficient of 0.6).[7]

Second, the country's exchange rate regime affected both the scale and scope of responses. Concerns regarding excessive credit growth were predominantly observed in countries with fixed exchange rate regimes, specifically from countries operating under formal currency boards (Bulgaria, Estonia or Lithuania) or quasi-currency boards (Latvia, Croatia[8]). Many of these economies experienced unprecedented capital inflows, which fueled the credit boom. Being unable to exploit interest rates or exchange rate tools, these countries introduced a wealth of various macroprudential and supervisory tools. Most of the measures also specifically targeted key aspects of credit developments, namely FX-denominated private borrowing. Bakker & Klingen (2012) emphasize that fixed exchange rates need not be a problem per se, but they do make it more difficult to address excessive capital inflows.

The policy measures employed in the region were generally reactive rather than proactive or counter-cyclical. There has been a controversy regarding the type and timing of policy responses. Adopting a fiscal perspective, Bakker & Klingen (2012) emphasized that public expenditure growth should have been more restrained during the boom years. If the surge in revenues had been used to accumulate greater fiscal surpluses, fiscal policy would not have further fueled overheating (Bakker & Klingen 2012). Based on the survey results,

[7] One reason for not overly strong correlation is that countries with similar credit dynamics exercised very different scale of policies (see LT and LV in Table 2.1). Second reason is also that not all measures are of an equal strength which can lead to spurious correlation results.

[8] The de jure and de facto regimes in Croatia differ markedly. The National Bank of Croatia de jure employs an exchange rate regime of managed floating. In light of the highly euroized financial system, Croatia de facto operates under a quasi-currency board that allows for exchange rate volatility to discourage one-way gambles and speculation and encourage FX hedging.

only Latvia undertook changes in taxation to discourage lending practices (the change in taxation targeted real estate transactions). Nevertheless, Martin & Zauchinger (2009) argue that even in the case of Latvia, the implementation of fiscal measures intended to simulate the economy amid the turmoil that followed the financial crisis proved a highly complex task, as the government had failed to accumulate sufficient reserves in good times.

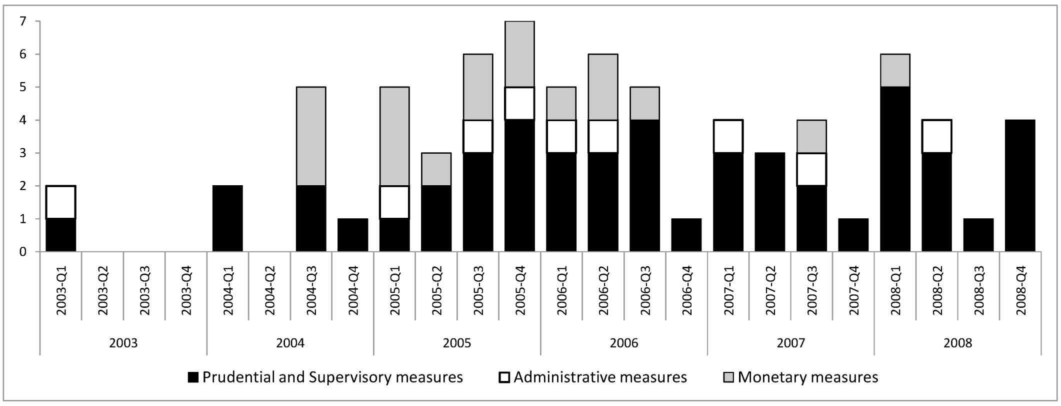
Regarding the reactiveness of the macroprudential and monetary stance, CEE policymakers devoted substantial effort to design prudential and supervisory measures in line with European best practices and Basel II requirements. The levels of capital buffers were higher than those listed in these practices and requirements. The rationale behind the more prudent stance adopted by certain economies again stems from the nature of the region (its relative immaturity, riskiness and turbulent credit developments).

Moreover, the reactive stance adopted by central authorities stemmed from the wide range of circumvention practices used by banks. The experiences of countries such as Croatia or Bulgaria indicate a shift in activities to less regulated segments of the financial system as a response to the measures. The problem was rooted in a lack of enforcement capacity and weak cross-border supervisory cooperation. This argument was prominently stressed in the literature prior to or after the financial meltdown (Hilbers *et al.* (2005), Bakker & Klingen (2012)). The lack of supervisory coordination contributed to the creation of loopholes such as the shift from FX-lending by local subsidiaries to direct lending by foreign parent banks or the shift to less regulated and supervised non-bank financial institutions (notably leasing companies) that conducted quasi-bank activities and fell outside the scope of regulation. Consequently, some countries reacted by implementing further measures to counter newly emerged adverse issues (broadening of the base for reserve requirements or extending the supervision). As a result, the success of most measures using bank credit data was short-lived. Ideally, one would need to use broader datasets (containing not only bank credit but also non-bank data) to fully assess the issue.[9]

Figure 2.4 illustrates the evolution of the measures used in the CEE region. The reactiveness of the measures can also be supported by their frequency. In

[9]The BIS constructed a database on total credit provided to the private sector, including direct, cross-border lending and credit provided by non-bank financial institutions to the private sector (Dembiermont et al., 2013). Unfortunately, this database currently covers only a sub-set of CEE countries (the Czech Republic, Hungary and Poland).

Figure 2.4: Number of policy measures over time in CEE (quarterly data)



particular, unless confronting a serious issue, most policy responses were "late risers". The peak of policy activities was in the second half of 2005 and the first half of 2006. One explanation for the relatively "late" action by national authorities was the lack of appropriate macroprudential frameworks that would have decreased the bias toward inaction. Clearly, however, during the pre-crisis period of 2003–2007, no country had such a framework, which has been under development in many countries since 2010 (Houben *et al.* 2012). With respect to specific types of responses, we can observe that monetary measures were among the first employed. Over time, most of these policies reached their limits, and the authorities turned to more specific prudential and supervisory tools later in the period. This is also because the traditional macroeconomic policy tools were not sufficiently powerful to slow the credit boom and policymakers decided to at least improve the resiliency of the banking sector, silently hoping for positive side effects of such measures in terms of decelerating credit growth.

A few economies facing the most serious external imbalances undertook more direct measures (credit ceilings or capital controls). The overall use of such measures does not strictly correspond to the data presented in Figure 2.4, as all of the modifications and amendments to existing measures taken in different periods are displayed. For the period under review, Croatia witnessed two credit ceiling periods (2003 and 2007–2009).[10] Further intervention occurred in Bulgaria (since March 2005, with further adjustments made in 2005 and 2006) and Romania (September 2005). In mid-2008, Lithuania also resorted

[10]The credit ceiling was only eliminated in November 2009. The elimination of the tax was delayed due to concerns that removing the tax would allow banks to depreciate the exchange rate.

to temporary direct measures designed to decelerate capital inflows into the banking sector (capital controls). In the following section, we examine the four subgroups of measures that were most widely adopted in CEE countries during the period under review (Table 2.2).

Table 2.2: Popularity of the policy measures

	Total usage	*Amount of countries*
Interest rate response	8 *	3
Reserve requirements	12 **	5
Capital requirements (higher/differentiated) or higher risk weights	12	8
Liquid asset requirements (introduction/tightening)	3	3
Tighter asset classification rules	3	2
Tighter provisioning rules	3	3
Tighter eligibility criteria for certain loans (via LTV, LTI etc.)	5	3
Tighter rules on valuation criteria	1	1
Measures targeted on FX borrowing	6	5
Soft measures - new non-binding guidelines for banks	13	9
Tighter supervision	7	4
Capital controls	1	1
Credit ceilings	7 ***	3
Change in taxes on real estate transactions	1	1

* The total number of interest rate responses may differ from the stated value. Three countries listed interest rate tightening as a policy measure they attempted; yet a majority of the central banks acknowledge they raised the key policy rate to affect inflationary pressure, influencing credit growth as a by-product.
** Five of which were changes in MRR in Croatia.
*** Two of which in Croatia; also includes changes and amendments to the MRR in Bulgaria.

2.4.1 Soft measures

The survey results revealed that soft measures were the most popular. Nine of the eleven countries issued non-binding guidelines for banks at least once over the 2003–2008 period. Moreover, many countries continued to pursue moral suasion and soft measures targeting domestic consumers. All of the guidelines were introduced in the latter part of the period (2006–2008). A proposed more prudent risk assessments and lending practices, with a particular emphasis on FX lending. Their main objective was to encourage banks to adopt new policies and procedures to identify, monitor and control the credit and FX risks of the borrowers.

Soft measures were also effectively combined with other instruments, such as the case of Poland.[11] Alternatively, non-binding guidelines were often succeeded by tighter supervisory rules. Yet, the evaluation of the measures suggests that they were not very effective. Estonia, which engaged in moral suasion for the entire period, admitted that the credit expansion continued nonetheless. Hungary attempted to improve consumer awareness of the underlying risks but also failed to achieve any palpable results. Yet, as the measures were generally implemented in the later phase of the period, the majority of their effects are difficult to distinguish from the impacts of the crisis.

2.4.2 Capital requirements and risk weights

Modification of capital requirements is among the most popular policy options. Our period, however, coincides with that in which CEE countries were to adopt the Basel II requirements. This may also account for the popularity of the measure. As this essay is not concerned with the impact of Basel II, we will concentrate on other modifications to capital requirements, namely those predominantly made to curb credit growth. Nevertheless, it is reasonable to stress that most of the economies studied here maintained a capital adequacy ratio well above 8%.

The survey results indicate that the vast majority of the measures were more concerned with adjusting risk weights. Higher risk weights were widely applied in two cases: real-estate related loans and FX loans. The first measure was applied in countries facing real estate booms in conjunction with credit booms (e.g., Estonia, Latvia, Lithuania and Bulgaria). Weights for real-estate related loans were occasionally increased to 100%. The measures generally targeted home mortgages or/and those on commercial property. In Bulgaria, these measures were jointly implemented with tighter eligibility criteria (the limit on LTV was reduced from 70% to 50%).

The latter measure was also popular in the case of real estate booms, as the largest portion of private FX loans were mortgages. For example, in 2008, Hungary increased capital requirements on loans denominated in Japanese Yen under Pillar 2 of Basel II. Croatia required the creation of additional capital buffers for loans to unhedged borrowers. Prior to Basel II, Croatia also required

[11] Recommendation S combined measures targeting FX borrowing (specifically by targeting unhedged households) and non-binding guidelines for banks. The measure called on banks to both assess and inform customers of FX risks. Among other guidelines, banks were asked to evaluate the ability of borrowers to repay FX loans in the event of a 20% depreciation of the zloty and an interest rate at least equal to the level of the zloty interest rate when granting the FX loans (National bank of Poland 2007).

higher risk weights for loans to unhedged borrowers (originally set at 25%, later increased to 50%). Subsequently, in 2006, it introduced guidelines for banks on the management of foreign-currency induced credit risk.

2.4.3 Reserve requirements

Four of the eleven central banks resorted to tightening reserve requirements to dampen the effect of the credit boom: Romania (2004–2005), Croatia (2004–2006), Estonia (2006) and Latvia (2004–2006). All of the changes occurred in the first half of the period studied, suggesting that RR could have been one of the first measures implemented. As the credit data show, however, the boom did not stop in 2006, rendering the overall effectiveness of such measures questionable.

This instrument falls into the category of monetary tools, which may also justify the discontinuation of its use after 2006. One reason is that RR levels in the CEE region were well above the euro area average, and their effectiveness was limited by further increases in the required levels. For example, the standard RR on liabilities denominated in domestic currency were set as high as 18% in Romania and Croatia and 15% in Estonia. In terms of overall quantitative constraint, this was neither the strongest nor the most popular measure. The rationale is that the most dangerous factor was not the pace of credit growth per se but the underlying currency and maturity mismatches. As a result, central authorities decided to act by broadening the reserve base (Latvia in 2005 and 2006, Romania twice in 2005), differentiation by deposit type (Latvia in 2005 and 2006) and differentiation by currency (Romania in 2004 and 2006).

The Croatian experience is particularly interesting, as the monetary authority reduced the minimum required reserve ratio multiple times over the period under study (counter-measure) while introducing new marginal reserve requirements (MRR) and special reserve requirements (SRR). Although both MRR and RR differentiated by currency have the same goal (to control excessive FX-denominated borrowing), the difference lies in the marginal character of MRR (additional requirements only apply to increased FX liabilities). Nonetheless, the further modifications were again feasible - broadening of the base, change in the reference period, etc. However, SRR were introduced only once (at a late stage of MRR implementation), and they called for special requirements of 55% on liabilities arising from issued securities. Again, they were also differentiated by currency.

The outcomes of the various RR measures did not meet expectations. As a positive development, Hilbers *et al.* (2005) acknowledge that the term structure of FX borrowings improved (e.g., Estonia). The overall effectiveness of RR was short-lived, as domestic actors rapidly adapted to the new constraints. Domestic subsidiaries circumvented the measures via externalizing a share of their FX loan portfolios to the balance sheets of foreign-owned parent banks or subsidiaries operated as their agents (primarily in the case of corporate clients).

Furthermore, activities were often shifted to the less regulated sector of leasing companies (for example, in Croatia or Bulgaria). Banks also began to engage in asset swaps, collateralization or accelerated NPL write-offs Hilbers *et al.* (2005). All of this adversely affected data transparency. As central authorities reacted to these efforts by broadening the reserve base, local agents found new means of circumventing these requirements.

2.4.4 Measures targeting FX borrowing

As discussed above, many of the tools described were intended to inhibit FX borrowing (special weights on capital requirements, targeted, non-binding guidelines or reserve requirements differentiated by currency). Additionally, the survey further requested central banks to provide information on whether they introduced additional measures targeting FX borrowing, primarily by targeting unhedged borrowers or tighter net open positions. Overall, five countries adopted one of the listed measures (Croatia, Latvia, Lithuania, Poland and Romania).

The measures generally managed to reduce the FX lending practices of subsidiary banks. In some cases, banks simply shifted their activities directly to their parent banks. However, Poland might represent a success, as the measures implemented there helped to shift foreign currency lending to domestic currency lending, which is easier to manage using conventional policy tools and which poses less risks, especially under a floating exchange rate regime.

2.5 Panel regression analysis

2.5.1 Data and methodology

Panel regression allows us to analyze the effect of the specific policy measures implemented across the CEE region to slow credit growth. As mentioned above, some countries did not attempt to combat excessive credit growth. Moreover, even after deciding to act, the measures implemented differed substantially across the region. The panel analysis thus enables us to analyze the treatment effect of specific policy tools using other countries and periods as controls.

The analysis is organized on two levels. First, we introduce a joint panel data analysis of all policy measures. Second, we analyze the policy measures on an individual basis, focusing on the effect of a single policy measure on credit growth. The first model (Equation 2.1) is specified as follows:

$$\Delta \mathbf{Y}_{i,t} = a + b\mathbf{X}_{i,t-1} + c\mathbf{Z}_{i,t-1} + d\mathbf{V}_{i,t} + \nu_i + \epsilon_{i,t} \tag{2.1}$$

$\Delta \mathbf{Y}_{i,t}$ represents annual private sector credit growth in a country i at time t. t. The matrix $\mathbf{X}$ is a set of dummy variables for all policy measures, which take a value of 1 during the period when a specific policy measure is effective and 0 otherwise. Furthermore, a number of CEE economies repeatedly adjusted or strengthened these policy measures. The effect of such policy tightening would not be captured by matrix $\mathbf{X}$. When applicable, matrix $\mathbf{Z}$ will capture policy strengthening.[12] Here, the dummy variables are constructed in a different manner than those in matrix $\mathbf{X}$. In matrix $\mathbf{X}$, we assign a value of 1 for an entire period when a policy tool is effective to capture the presence of the measure. In matrix $\mathbf{Z}$, we exclusively focus on the effect of policy tightening, i.e., a dummy variable takes a value of 1 if the measure is strengthened and remains 1 for a period of three months, reverting to 0 thereafter.

Appendix B provides a detailed explanation of how the policy measures reviewed in the survey are used and grouped in the panel data regression analysis. Provided that a measure was never tightened over the entire period, we consider matrix $\mathbf{X}$ only. The majority of the measures are used in the same manner as reported in the survey. In the event that the structure differs, an explanation is provided in the form of a note (Appendix B).

Matrix $\mathbf{V}$ presents a set of main macroeconomic controls included in the

[12] Galac (2010) and Kraft & Galac (2011) also employed the concept of policy strengthening when assessing the effectiveness of specific policy measures used in Croatia.

panel regression. We use GDP growth, lending rate and exchange rate volatility. The choice of controls is dependent on data available for all listed countries throughout the full period. In the robustness section, we replace lending rate levels with differences and this change does not change the results.

The second model (Equation 2.2) considers the individual effect of a specific policy instrument. An analogous approach is applied by Lim *et al.* (2011), Galac (2010) and Kraft & Galac (2011). The specification of the model is as follows:

$$\Delta \mathbf{Y}_{i,t} = a + b\hat{\mathbf{X}}_{i,t-1} + c\hat{\mathbf{Z}}_{i,t-1} + d\mathbf{V}_{i,t} + e\mathbf{U}_{i,t} + \nu_i + \epsilon_{i,t} \tag{2.2}$$

The dependent variable, private sector credit growth, and the macro-control variables in matrix $\mathbf{V}$ remain unchanged. Matrix $\hat{\mathbf{X}}$ is now adjusted to only include one instrument per regression. When applicable, matrix $\hat{\mathbf{Z}}$, reflecting decisions to strengthen policy measures (again adjusted to only include one policy measure per regression), is also used in the same manner as in Equation 2.1.

Because the policy measures were often introduced jointly or when other measures were already present, we also need to account for the effect of other active policy measures. Thus, matrix $\mathbf{U}$ controls for the effect of other policy tools at time t. Here, dummy variables take a value of 1 if other measures to counter credit growth were simultaneously in force and 0 otherwise.

Both models are estimated by using generalized method of moments (GMM) estimation following Arellano & Bover (1995) and Blundell & Bond (1998). We use 1-12 lags of credit growth and policy dummies as GMM instruments for first difference equations. We repeated our calculations for different structure of lags as well as within group estimator and the results stay robust to the benchmark.

Some caveats are in order. First, one of the major challenges when analyzing the introduction of policy to limit credit growth is endogeneity, i.e., policy actions are not randomly assigned in time and across countries. Countries which resort to a policy intervention tend to experience more pronounced credit booms. One possible remedy applied in this essay but also by Brockmeijer *et al.* (2011) or Cerutti *et al.* (2015) is to use GMM estimation technique.[13]

Second, our results should be read as average outcomes for a group of countries, and not necessarily for individual economies. While we recognize impor-

[13] In terms of an ideal policy experiment, a desired way would be to move to a more granular level of data, i.e. rich dataset on bank-level or loan-level credit. This, unfortunately to the best of our knowledge is not available for our set of countries or time horizon.

tance of country event studies, our aim is to observe general trends over the group of economies in the emerging Europe prior to the crisis.

The analysis is based on monthly data from 11 CEE economies over the period 2003–2007.[14] The values of the policy dummies are obtained via the direct survey presented in the previous chapter. The dependent variable and macro and macro-control variables are obtained from the IMF IFS and the ECB (see the data table in Appendix A).

2.6 Results

Table 2.3 presents the results of the first specification which evaluates an overall effectiveness of the policy measures used in the period 2003–2007, while Table 2.4 provides detailed results of the second speficiations, which reflects the analysis of individual policy measures. Two policy measures have negative and statistically significant estimates suggesting positive effect on taming credit growth: (i) provisioning rules / asset classification and (ii) limits on LTV/LTI. Lim *et al.* (2011) further find statistical evidence that caps on eligibility criteria reduce the pro-cyclicality of credit. The economic significance of the policy variables is relatively large: in periods where tighter asset classification and provisioning rules were in effect, credit growth was approximately 14–16% lower, while credit growth was approximately 12–13.5% lower during periods with stricter limits on LTV/LTI.

The statistically significant coefficient for credit ceilings has an incorrect (positive) sign, suggesting that this measure was not effective, and thus the positive sign may capture residual endogeneity, as the measure was applied in periods of high credit growth. A visual inspection of the data suggests that credit ceilings might have had a short-term effect, which did not, however, persist over the entire period during which such an instrument was in effect. This is in line with those of other studies. Lim *et al.* (2011) find no statistical evidence that credit ceilings were effective in slowing credit growth.[15] Galac

[14] The data series end in December 2007. The analysis was also performed over a longer period (2003–2008), which yielded quantitatively similar results. Nonetheless, it is not an easy task to clearly distinguish the effect of the crisis from the effect of the policy intervention in 2008. Moreover, some measures applied in 2008 might already have been motivated by the desire to prevent a credit crunch rather than taming credit growth, such as the temporary introduction of capital controls in Lithuania in June 2008. As a result, this essay exclusively focuses on the effects of policy measures until December 2007.

[15] However, the authors confirm the effect of credit ceilings in reducing the procyclicality of credit – credit ceilings GDP (Lim *et al.* 2011).

Table 2.3: Overall evaluation of the effectiveness of the policy measures

	(1) Credit growth$_{i,t}$	(2) Credit growth$_{i,t}$
Reserve requirements$_{t-1}$	0.0122	0.00201
	(0.0310)	(0.0255)
Capital requirements$_{t-1}$	-0.00154	-0.000331
	(0.0327)	(0.0315)
Provisioning rules & asset classification$_{t-1}$	-0.164**	-0.151**
	(0.0739)	(0.0659)
Limits on LTV/ LTI$_{t-1}$	-0.0948	-0.135**
	(0.0560)	(0.0539)
FX measures$_{t-1}$	-0.0101	-0.00153
	(0.0655)	(0.0679)
Supervision$_{t-1}$	0.0112	0.0348
	(0.0542)	(0.0412)
Credit ceilings$_{t-1}$	0.0452**	0.0625*
	(0.0204)	(0.0315)
Reserve requirements strengthening$_{t-1}$		0.0186
		(0.0218)
Capital requirements strengthening$_{t-1}$		0.0144
		(0.00983)
Limits on LTV/ LTI strengthening$_{t-1}$		0.0806
		(0.0465)
FX measures strengthening$_{t-1}$		-0.0351
		(0.0225)
Supervision strengthening$_{t-1}$		-0.0313
		(0.0497)
Credit ceilings strengthening$_{t-1}$		-0.0667
		(0.0663)
Macro controls[a]	Yes	Yes
Country FE	Yes	Yes
Observations	649	649
Number of countries	11	11
Joint significance[b]	0.000	0.000
Serial correlation[c]	0.0378	0.0999

Reported coefficients are based on Equation 2.1. Difference GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.

[a]Macro controls include GDP growth, lending rates and exchange rate volatility. [b]Reports p-values for the null hypothesis that measures are jointly not-significant (zero). [c]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 2.4: Regression analysis for individual policy measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Credit growth$_{i,t}$			
Reserve requirements$_{t-1}$	-0.00753						
	(0.0509)						
Reserve requirements strengthening$_{t-1}$	0.0192						
	(0.0197)						
Capital requirements$_{t-1}$		-0.0219					
		(0.0405)					
Capital requirements strengthening$_{t-1}$		-0.00606					
		(0.0121)					
Provisioning rules & asset classification$_{t-1}$			-0.140**				
			(0.0601)				
Limits on LTV/ LTI$_{t-1}$				-0.122**			
				(0.0475)			
Limits on LTV/ LTI strengthening$_{t-1}$				0.0365			
				(0.0313)			
FX measures$_{t-1}$					-0.00355		
					(0.0689)		
FX measures strengthening$_{t-1}$					-0.0270		
					(0.0297)		
Supervision$_{t-1}$						-0.0479	
						(0.0452)	
Supervision strengthening$_{t-1}$						-0.0388	
						(0.0719)	
Credit ceilings$_{t-1}$							-0.0154
							(0.0345)
Credit ceilings strengthening$_{t-1}$							-0.0508
							(0.0576)
Other measures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls[a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	649	649	649	649	649	649	649
Number of countries	11	11	11	11	11	11	11
Joint significance[b]	0.351	0.703	0.000782	1.29e-05	0.730	0.155	0.123
Joint significance[c]	0.335	0.864		3.23e-05	0.585	0.273	0.220
Serial correlation[d]	0.0143	0.00900	0.0150	0.153	0.0166	0.0570	0.00808

Reported coefficients are based on Equation 2.2. Difference GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.

[a]Macro controls include GDP growth, lending rates and exchange rate volatility. [b]Reports p-values for the null hypothesis that measures are jointly not-significant (zero). [c]Reports p-values for the null hypothesis that measures and measure strengthening are jointly not-significant (zero). [d]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

(2010) and Kraft & Galac (2011) also report that credit ceilings in Croatia were not very effective in curbing overall private sector credit growth. In the case of Croatia, Kraft & Galac (2011) further divide credit growth into corporate and household credit. Only when analyzing the sectors separately do the authors obtain strong evidence that household borrowing slowed when ceilings became active.

Other measures do not appear to significantly affect credit growth. The results on capital requirements suggest that they have very little effect, similar to the results in Lim *et al.* (2011). Generally, however, the empirical evidence suggests that although the measures were not particularly successful in curbing credit booms, capital requirements improved the stability of the financial system by creating buffers to cope with the subsequent credit busts (Dell'Ariccia *et al.* 2012). Moreover, Vandenbussche *et al.* (2015) demonstrate that higher minimum capital adequacy requirements can tame house price inflation. Further, reserve requirements are not observed to have an impact on taming credit growth. This result may be partly driven by the popularity of the measure (overall, we report 12 RR in 5 of the 11 countries considered) over the entire period of excessive credit growth, as it becomes difficult to disentangle their individual effect. Furthermore, RR were often used in conjunction with other measures and in overlapping periods, which makes their assessment very challenging. Vandenbussche *et al.* (2015), however, find statistically significant effects of marginal reserve requirements targeting specific excesses, such as those related to credit growth or foreign funding, on house price inflation. Neither tighter supervision nor FX measures indicate any influence on aggregate credit growth. Interestingly, the results imply that in the case of FX measures, exchange rate volatility did not play a role. These conclusions are also in line with the findings of Lim *et al.* (2011).

Given the difficulty of disentangling the individual effects of various policy variables and as a robustness check, we also ran joint statistical significance tests for the packages of measures implemented simultaneously for both models. The joint significance test indicates that tighter asset classification and provisioning rules and the limits on LTV/LTI might have had an effect on credit growth in conjunction with other measures applied simultaneously.

Additionally, our results are robust in terms of (i) methodology (GMM vs within group estimates), (ii) macroeconomic controls, (iii) lag structure of policy dummies, and (iv) country composition (including/excluding the Czech Republic). Main robustness resutls are reported in Appendix C.

2.7 Conclusions

This essay discusses the policy measures implemented in CEE to dampen private sector credit dynamics. The analysis is based on an original survey that incorporated the policy experiences of eleven central banks in CEE over the period 2003–2008. Overall, our findings reveal 82 policy measures used both separately and in combination. We also find substantial heterogeneity in the amount frequency of policy actions across the region. The group of most popular responses includes tightening reserve requirements, capital requirements, soft measures or specific measures targeting foreign-currency denominated loans. We report the most active policy involvement in countries with high overall credit booms or excessive FX-lending (e.g. Croatia or Latvia) while countries with less pronounced credit dynamics hardly used new policy actions in the respective period. These conclusions are also in line with the recent publications at the international level on the use and effectiveness of macroprudential policies (CGFS (2010), CGFS (2012), CGFS (2016), ESRB (2014), IMF-FSB-BIS (2016)).

We assessed the effectiveness of the policy measures, combining the survey results with a wider set of available macroeconomic data (private credit, GDP growth, lending rate and exchange rate volatility) in a dynamic panel data framework. We focused on both the effect of policy implementation and the effect of strengthening these policies on the level of bank credit extended to the private sector. The empirical analysis identified two main instruments that reduced the rate of credit growth in CEE, namely tighter asset classification and provisioning rules, and tighter eligibility criteria such as limits on LTV/LTI. As it is difficult to disentangle the individual effects of various instruments because they were often applied in conjunction, the possibility that other measures might also have contributed to decelerating credit growth in CEE countries when jointly applied with the above-mentioned instruments cannot be ruled out.

However, while there might have been an effect on bank credit growth, the policy measures were often circumvented via direct, cross-border credit from foreign banks and credit provided by domestic, non-bank financial companies. Nevertheless, we also acknowledge that specific tools, such as tighter capital requirements or higher risk weights, may have improved the resiliency of the financial sector and the economy's ability to cope with the financial distress.

Appendix A: Data table

Matrix	Variable	Source	Type (note)	Mean	Standard deviation
ΔY	Annual private sector credit growth	IMF, International Financial Statistics, Claims on private sectors	Monthly data	0.30	0.17
X, Z	Reserve requirements Capital requirements Provisioning rules & asset classification Limits on LTV/LTI FX measures Supervision Credit ceiling	Direct survey	Monthly data (dummy variables)		
V	GDP growth	IMF International Financial Statistics, Gross Domestic product, Nominal	Quarterly data (linearly interpolated into monthly series)	0.12	0.06
	Lending rate	IMF, International Financial Statistics, FILR: Interest rates, Lending rate	Monthly data	8.74	4.32
	Exchange rate volatility	ECB, Euro foreign rexchange reference rates.	Daily data (standard deviation)	12.41	66.10

Appendix B: Policy measures in the survey

	Panel regression		
	Used in regression (matrix X)	Policy strengthening (matrix Z)	Notes
Monetary measures			
Interest rate response	No	No	The prime lending rate is used as one of the macro-control variables. Interest rate tightening was not used as a primary response to the credit growth per se.
Reserve requirements Changes in the required level Differentiated by currency Differentiated by deposit type Broaden the reserve base	Yes: Reserve requirements	Yes: Reserve requirements strengthening	One variable for all types of RRs (including MRR in case Croatia).
Macroprudential and supervisory measures			
Capital requirements or higher risk weights	Yes: Capital requirements	Yes: Capital requirements	
Liquid asset requirements	No	No	Not used over the period 2003–2007. As late as July 2008, Poland introduced the measure to counter credit growth. Croatia: LAR lowering (countermeasure) in a number of steps in exchange for other policy measures.
Tighter asset classification rules	Yes: Provisioning	No	One variable controlling for both asset classifi-
Tighter provisioning rules	rules and asset classification		cation and provisioning rules. No policy strengthening.

Tighter eligibility criteria Limit on LTV Limit on LTI	Yes: Limits on LTV/LTI	Yes: Limits on LTV/LTI strengthening	One variable
Tighter rules on valuation criteria	No	No	Not used over the period 2003–2007.
Measures targeted on FX borrowing Targeting unhedged borrowers Tighter net open position limits	Yes: FX measures	No	One variable No policy strengthening.
Soft measures: non-binding guidelines for banks	No	No	Not used in regressions as almost all countries applied over the period under review.
Tighter supervision	Yes: Supervision	Yes: Supervision strengthening	
Administrative and other measures			
Capital controls	No	No	Not used over the period 2003–2007. Lithuania implemented capital controls in June 2008.
Credit ceilings	Yes: Credit ceilings	Yes: Credit ceilings strengthening	
Change in taxes on real estate transactions	No	No	Rarely used. Only in the case of Latvia (July 2007) as a part of its Anti-inflation Plan.

Appendix C: Robustness

Table 2.6: Robustness: Different lag structure

	(1)	(2)	(3)
		Credit growth	
Reserve requirements$_{t-1}$	0.0106	0.0390	0.0452
	(0.0309)	(0.0496)	(0.0562)
Reserve requirements$_{t-2}$		-0.0333	-0.0106
		(0.0377)	(0.0215)
Reserve requirements$_{t-3}$			-0.0333
			(0.0455)
Capital requirements$_{t-1}$	-0.00285	-0.0112	-0.0139
	(0.0319)	(0.0323)	(0.0307)
Capital requirements$_{t-2}$		0.0106	0.0388*
		(0.0259)	(0.0214)
Capital requirements$_{t-3}$			-0.0273
			(0.0414)
Provisioning rules & asset classification$_{t-1}$	-0.167**	-0.100***	-0.111***
	(0.0716)	(0.0258)	(0.0273)
Provisioning rules & asset classification$_{t-2}$		-0.0640	-0.0422
		(0.0752)	(0.0244)
Provisioning rules & asset classification$_{t-3}$			-0.00191
			(0.0705)
Limits on LTV/ LTI$_{t-1}$	-0.0937	-0.0815	-0.0862
	(0.0554)	(0.0656)	(0.0642)
Limits on LTV/ LTI$_{t-2}$		-0.0166	0.00895
		(0.0802)	(0.0283)
Limits on LTV/ LTI$_{t-3}$			-0.0322
			(0.0684)
FX measures$_{t-1}$	-0.0119	-0.0286	-0.0268
	(0.0650)	(0.0544)	(0.0551)
FX measures$_{t-2}$		0.0199	-0.00520
		(0.0219)	(0.0114)
FX measures$_{t-3}$			0.0293*
			(0.0149)
Supervision$_{t-1}$	0.0116	0.0142	0.0200
	(0.0539)	(0.0612)	(0.0624)
Supervision$_{t-2}$		0.00336	-0.0237
		(0.0688)	(0.0326)
Supervision$_{t-3}$			0.0316
			(0.0564)
Credit ceilings$_{t-1}$	0.0478**	0.0759*	0.0766*
	(0.0200)	(0.0382)	(0.0368)
Credit ceilings$_{t-2}$		-0.0352	-0.0107
		(0.0336)	(0.0212)
Credit ceilings$_{t-3}$			-0.0344***
			(0.00900)
Macro controls[a]	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	649	638	627
Number of countries	11	11	11

[a]Macro controls include GDP growth, lending rates and exchange rate volatility.
Based on Equation 2.1. Difference GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998). Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.

Table 2.7: Robustness: Methods and macro controls

	(1) Benchmark	(2)	(3)	(4) Benchmark	(5)	(6)
Reserve requirements$_{t-1}$	0.0106	0.0108	0.0184	0.000372	0.000882	0.0103
	(0.0309)	(0.0151)	(0.0323)	(0.0257)	(0.0162)	(0.0295)
Capital requirements$_{t-1}$	-0.00285	-0.00673	0.0195	-0.00171	-0.00586	0.0184
	(0.0319)	(0.0139)	(0.0280)	(0.0307)	(0.0144)	(0.0266)
Provisioning rules	-0.167**	-0.163***	-0.124	-0.154**	-0.149***	-0.111
& asset classification$_{t-1}$	(0.0716)	(0.0266)	(0.0970)	(0.0637)	(0.0269)	(0.0850)
Limits on LTV/ LTI$_{t-1}$	-0.0937	-0.092***	-0.129**	-0.133**	-0.131***	-0.162**
	(0.0554)	(0.0238)	(0.0546)	(0.0529)	(0.0263)	(0.0553)
FX measures$_{t-1}$	-0.0119	-0.0111	0.00476	-0.00367	-0.00282	0.0162
	(0.0650)	(0.0142)	(0.0712)	(0.0674)	(0.0155)	(0.0744)
Supervision$_{t-1}$	0.0116	0.00942	0.0402	0.0342	0.0308	0.0637
	(0.0539)	(0.0232)	(0.0508)	(0.0411)	(0.0246)	(0.0404)
Credit ceilings$_{t-1}$	0.0478**	0.0472***	0.0408**	0.0654*	0.0647***	0.0562*
	(0.0200)	(0.0167)	(0.0151)	(0.0306)	(0.0176)	(0.0262)
Reserve requirements				0.0194	0.0191	0.0100
strengthening$_{t-1}$				(0.0220)	(0.0139)	(0.0230)
Capital requirements				0.0150	0.0151	0.0107
strengthening$_{t-1}$				(0.00968)	(0.0179)	(0.0142)
Limits on LTV/ LTI				0.0821	0.0792**	0.0568
strengthening$_{t-1}$				(0.0464)	(0.0313)	(0.0499)
FX measures				-0.0335	-0.0337	-0.0494*
strengthening$_{t-1}$				(0.0227)	(0.0257)	(0.0242)
Supervision				-0.0292	-0.0294	-0.0605
strengthening$_{t-1}$				(0.0504)	(0.0262)	(0.0348)
Credit ceilings				-0.0680	-0.068***	-0.0682
strengthening$_{t-1}$				(0.0645)	(0.0215)	(0.0675)
GDP growth	1.514***	1.516***	0.747***	1.456***	1.461***	0.724***
	(0.304)	(0.151)	(0.175)	(0.300)	(0.152)	(0.184)
Lending rate	-0.019***	-0.019***		-0.019**	-0.019***	
	(0.00577)	(0.00246)		(0.00621)	(0.00251)	
Δ Lending rate			0.0124			0.0113
			(0.00696)			(0.00679)
Exchange rate	-0.0002**	-0.0002***	-0.0004***	-0.0002**	-0.0002***	-0.0004***
volatility	(7.26e-05)	(7.30e-05)	(0.000106)	(7.83e-05)	(7.30e-05)	(9.86e-05)
Observations	649	660	638	649	660	638
R-squared		0.273			0.297	
Number of countries	11	11	11	11	11	11
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	GMM	OLS FE	GMM	GMM	OLS FE	GMM

Based on Equation 2.1. Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.

Table 2.8: Robustness: Overall evaluation of the effectiveness of the policy measures (excl. CZ)

	(1) Credit growth	(2) Credit growth
Reserve requirements$_{t\text{-}1}$	0.0105	0.000636
	(0.0315)	(0.0264)
Capital requirements$_{t\text{-}1}$	0.00214	0.00382
	(0.0293)	(0.0278)
Provisioning rules & asset classification$_{t\text{-}1}$	-0.166**	-0.152**
	(0.0724)	(0.0639)
Limits on LTV/ LTI$_{t\text{-}1}$	-0.0950	-0.136**
	(0.0568)	(0.0553)
FX measures$_{t\text{-}1}$	-0.00841	2.11e-05
	(0.0649)	(0.0678)
Supervision$_{t\text{-}1}$	0.0144	0.0383
	(0.0561)	(0.0435)
Credit ceilings$_{t\text{-}1}$	0.0484**	0.0656*
	(0.0198)	(0.0306)
Reserve requirements strengthening$_{t\text{-}1}$		0.0176
		(0.0220)
Capital requirements strengthening$_{t\text{-}1}$		0.0129
		(0.00925)
Limits on LTV/ LTI strengthening$_{t\text{-}1}$		0.0833*
		(0.0447)
FX measures strengthening$_{t\text{-}1}$		-0.0341
		(0.0244)
Supervision strengthening$_{t\text{-}1}$		-0.0321
		(0.0495)
Credit ceilings strengthening$_{t\text{-}1}$		-0.0685
		(0.0651)
GDP growth	1.338***	1.268***
	(0.232)	(0.213)
Lending rate	-0.0169**	-0.0164**
	(0.00550)	(0.00595)
Exchange rate volatility	-0.000217**	-0.000195**
	(7.28e-05)	(7.86e-05)
Observations	590	590
Number of countries	10	10
Country FE	Yes	Yes

Based on Equation 2.1. Difference GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998). Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.

Table 2.9: Robustness: Regression analysis for individual policy measures (excl. CZ)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Credit growth			
Reserve requirements$_{t-1}$	-0.00517						
	(0.0522)						
Reserve requirements strengthening$_{t-1}$	0.0166						
	(0.0191)						
Capital requirements$_{t-1}$		-0.0174					
		(0.0404)					
Capital requirements strengthening$_{t-1}$		-0.00816					
		(0.0121)					
Provisioning rules & asset classification$_{t-1}$			-0.141**				
			(0.0596)				
Limits on LTV/ LTI$_{t-1}$				-0.116**			
				(0.0471)			
Limits on LTV/ LTI strengthening$_{t-1}$				0.0395			
				(0.0294)			
FX measures $_{t-1}$					0.00101		
					(0.0697)		
FX measures strengthening$_{t-1}$					-0.0287		
					(0.0312)		
Supervision$_{t-1}$						-0.0459	
						(0.0491)	
Supervision strengthening$_{t-1}$						-0.0430	
						(0.0706)	
Credit ceilings$_{t-1}$							-0.0154
							(0.0334)
Credit ceilings strengthening$_{t-1}$							-0.0521
							(0.0581)
Other measures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls[a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	590	590	590	590	590	590	590
Number of countries	10	10	10	10	10	10	10
Joint significance[b]	0.460	0.775	0.000691	1.94e-05	0.785	0.219	0.142
Joint significance[c]	0.428	0.885		5.00e-05	0.626	0.360	0.250
Serial correlation[d]	0.0128	0.00948	0.0117	0.0733	0.0168	0.0625	0.00675

Reported coefficients are based on Equation 2.2. Difference GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator.
Robust standard in parentheses ***p<0.01, **p<0.05, *p<0.1.
[a]Macro controls include GDP growth, lending rates and exchange rate volatility.
[b]Reports p-values for the null hypothesis that measures are jointly not-significant (zero).
[c]Reports p-values for the null hypothesis that measures and measure strengthening are jointly zero.
[d]Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Chapter 3

Banking crises in EMEs and credit-based early warnings

This essay explores the role of credit-based variables as early warning indicators (EWIs) of banking crises in the context of emerging economies. The signaling performance is evaluated by using receiver operating characteristics (ROC) curve and area under the curve (AUC). Our results show that nominal credit growth and the change in credit-to-GDP ratio have the best signaling properties and significantly outperform the credit-to-GDP gap in almost all specifications for policy-relevant longer horizons. These findings are in stark contrast with the results on advanced economies where the credit-to-GDP gap is the single best performing EWI. Our results emphasize the importance of caution when applying statistical methods calibrated for advanced markets to emerging economies and explore credit-based alternatives for EME policymakers.

This essay is an extension my working paper "Banking crises in emerging economies: Can credit variables work as early warnings"(IES WP, 27/2015) and a paper jointly written with Adam Geršl entitled "Constructing credit-based early warning indicators of banking crises: guidance for emerging Europe" (submitted to a journal). We would like to thank the participants of seminars at Charles University, Sogang University and Waseda University for useful comments. This work was supported by the Grant Agency of Charles University (project GAUK No. 564612).

3.1 Introduction

As a reaction to the financial crisis, much of the research has been focused on how to mitigate the episodes of banking distress. Basel Committee on Banking Supervision, as a part of Basel III, has proposed the countercyclical capital buffer (CCB) as an instrument to make the banks more resilient in times of crises (BCBS 2010). To do so, banks are required to create capital reserves in good times and use this capital in times of distress. Hence, the design of a well-functioning CCB requires a conditioning variable that would be able to capture the build-up of the banking system vulnerabilities. At the same time, research on early warnings indicators has been flourishing both across academia and policymakers.

Much has been done in case of developed economies. BCBS (2010) proposes the activation of the macroprudential CCB to be mainly based on credit-to-GDP gap. In the underlying research, this variable shows the best signallng performance although some caveats are in order. Edge & Meisenzahl (2011) and Geršl & Seidler (2015) emphasized potential weaknesses of the statistical technique behind the construction of the gap indicator, in particular the reliability of end-of-sample estimates and quality of the information of the time series for converging countries undergoing financial deepening. This is especially relevant for emerging markets countries, which are currently designing their macroprudential policy frameworks and are looking for robust variables with good signaling properties to support their policy decision-making.

The objective of this essay is to explore signaling abilities of credit variables in case of emerging economies. We focus on the episodes of banking crisis in 36 emerging economies over the period 1987–2015. We contribute to the literature in two ways. First, while the up-to-date research on early warning indicators (EWIs) has mostly been focused on advanced economies or mixed samples, this paper has a direct focus on emerging markets only. Therefore, potential drawbacks of statistical techniques and data quality remain in the center of attention. Second, building on the Credit to the Non-Financial Sector BIS database (Dembiermont *et al.* 2013), this essay works with long time series on credit data for emerging markets both on total and banking credit to the private non-financial sector. We combine data for emerging markets available in the BIS database with data from national sources on countries from emerging Europe and Caucasus. As a result, we are able to test signaling properties of credit variables on countries that were previously omitted from the samples.

To evaluate the quality of the signals we employ the receiver operating characteristics (ROC) curve and compute the area under the curve (AUC). This method provides a simple and easy-to-interpret approach and it is gaining more ground among the very recent EWIs literature (Elliott & Lieli (2013), Drehmann & Juselius (2014), Giese *et al.* (2014), Žigraiová & Jakubík (2015)). Our findings show that the credit-to-GDP gap as proposed by Basel III does not prove to be the best performing indicator among emerging economies. Nominal credit growth and growth in credit-to-GDP ratio provide superior results to the credit-to-GDP gap under all policy-relevant time specifications and for both bank and total credit. This conclusion challenges previous finding for advanced economies (Drehmann *et al.* (2010), Drehmann *et al.* (2011) and Drehmann & Tsatsaronis (2014)) and emphasizes the importance of caution when applying statistical methods calibrated for advanced markets to emerging economies.

The remainder of the essay is organized as follows: Section 3.2 presents the relation and the value added with respect to the up-to-date literature in the areas. Section 3.3 briefly introduces the data and methodology used. Section 3.4 provides the main findings, Section 3.5 includes robustness test and Section 3.6 concludes.

3.2 Review of literature

This essay closely links to two main strands of literature. The first strand stems from the discussion regarding the construction of Basel III countercyclical capital buffer (CCB). The effective use of the CCB requires an underlying variable that would signal the build-up of financial distress. The original research of the Bank for International Settlements (Borio & Lowe (2002), Drehmann *et al.* (2010), Drehmann *et al.* (2011)) presents an extensive analysis of the properties of a wide range of potential underlying variables from system-wide aggregate macroeconomic conditions, banking sector indicators to bank-specific costs of funding. Their findings consistently reveal that credit variables tend to perform the best at signaling the build-up of financial distress. In particular, credit-to-GDP gap provides the most promising results.

This result is consistent with the later findings by Babecký *et al.* (2014) and Behn *et al.* (2013) who work with the EU economies. Giese *et al.* (2014) who analyze the United Kingdom conclude that credit-to-GDP gap worked well in providing an advanced signal for past UK crises but they question its future signaling success.

The second stream of literature focuses on a critique of credit-to-GDP gap as an early-warning variable for banking crises in the context of emerging economies. Credit-to-GDP gap is computed as a deviation of the credit-to-GDP ratio from its long-term trend. Technically, trend is calculated by applying a one-sided rolling Hodrick-Prescott (HP) filter with lambda set to 400,000 in quarterly data. This HP filter, however, requires sufficiently long time series of at least 10 years of available data (Borio & Lowe (2002), later also in BCBS (2010)).

This part of literature warns against the appropriateness of one-sided HP-filtered technique to calculate the credit-to-GDP gaps in emerging market environment. Apart from potential length of data series, the filtering technique is not adequately equipped to capture financial deepening (convergence) of the economies. Geršl & Seidler (2010) suggest alternative method based on calculating credit-to-GDP gap with respect to economic fundamentals of a country. Contrary to the traditional credit-to-GDP gap indicator, Jakubík & Moinescu (2015) propose a novel approach for estimating the equilibrium level of credit growth. A study by Drehmann & Tsatsaronis (2014) addresses a number areas of criticism for credit-to-GDP gap including its applicability in case of emerging economies. According to their results, credit-to-GDP gap performs well for emerging economies, albeit not as well as it does for the group of advanced economies.

In this essay, we exploit the BIS database on long series on credit to the private non-financial sector (Dembiermont *et al.* 2013) that provides longer time series on both total and banking credit to the private non-financial sector. In addition, we collect more credit variables for the countries of emerging Europe and Caucasus. We aim to once again look into the signaling properties of various credit variables for as many emerging economies as the data availability permits and provide a comparison with the original results published for the advanced economies.

3.3 Data and methodology

This paper focuses on a set of 36 emerging economies[1], combining those covered by the BIS data on total credit and those from emerging Europe and Caucasus, for which we collected data from various national and international sources. We focus on the time period of 1987Q1–2015Q4 or shorter subject to data availability (see Appendix A).

The point of departure for the analysis is the signal extraction method as introduced by Kaminsky & Reinhart (1999). Following this idea, there are four important points of judgment that need to be stipulated: (i) definition of the crisis, (ii) selection of the potential leading variables, (iii) definition of the signal, and (iv) "reasonable" time period (horizon) to test the signaling quality.

3.3.1 Definition of the crisis

As to the identification of banking crises, existing literature on banking crises provide heterogeneous definitions relying on the performance of selected variables vis-à-vis different thresholds, expert judgments, etc. Babecký *et al.* (2014) construct a quarterly database of the occurrence of banking, debt, and currency crises for a panel of 40 countries currently regarded as developed, over 1970–2010. The authors compile existing pool for crisis databases and complement it with a comprehensive survey among country experts from all countries in the sample. Their results confirm substantial variation in the definition of crises across the published studies.

Unfortunately, to the best of our knowledge, there is not a fully exhaustive database in the spirit of Babecký *et al.* (2014) for emerging markets. To overcome this potential weakness, we first rely on the seminal work by Laeven & Valencia (2012), which covers the countries analyzed in our sample fairly well. Second, we complement their dating with additional information from other sources. This database is used in our main analysis.

In total, we identify 43 crises in our sample since (see Appendix B). However, given the data availability, we only use a subset of 14 crises in the signaling analysis (out of which six are related to the recent global financial crisis). The other crises happened at the beginning of our sample (in 1980s and in early

[1] Albania, Argentina, Armenia, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, Chile, China, Croatia, the Czech Republic, Estonia, Georgia, Hong Kong SAR, Hungary, India, Indonesia, Israel, Korea, Latvia, Lithuania, Macedonia, Malaysia, Mexico, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, South Africa, Thailand, Turkey and Ukraine.

1990s, including those related to the economic transition in emerging Europe and Caucasus), and we do not have sufficient credit data before these crises to be able to include them into our analysis.

Third, we acknowledge that even a combination of Laeven & Valencia (2012) and additional national data may still pose some questions regarding the underlying coding methodology. Uniformly applied statistical measures may not be able to fully distinguish the episodes of genuine banking crises from the episodes of privatization and restructuring which were for instance common in emerging Europe in late 1990s. To address this issue further, we also include analysis against the crisis database of Babecký *et al.* (2014) who are able to provide a finer distinction of crises by merging multiple data sources and correcting them with additional local expert judgment. Although Babecký *et al.* (2014) focuses on 40 countries which are currently regarded as developed, there is certain overlap with our sample (most notably for emerging Europe). As a consequence, we provide results for this sub-sample of EMEs in the Robustness section.

An additional point of concern also highlighted by Babecký *et al.* (2014) is a greater discrepancy in the determination of crisis end-points. We attempt to address this potential weakness in two ways. First, as discussed above we make use of an alternative database by Babecký *et al.* (2014) with finer correction for end-points in the robustness. Second, we work with two different definition of crisis signals by focusing either on (i) on the full crisis horizon, (ii) or only on the starting point. This strategy is further explained in the below in section 3.3.4. Time Horizon.

At last, following Bussière & Fratzscher (2006), the signaling variables from the crisis periods are not used and we also drop 8 quarters after the end of the crisis as a potential post-crisis bias period.

In this essay we focus on banking crises. Banking crises, however, also then to occur simultaneously with currency or sovereign debt crises (twin crises). Kaminsky & Reinhart (1999) report that banking-sector distress is not only generally followed by a currency crisis, but it also helps to predict them. A currency crisis, on the other hand, does not help to predict the banking crises, but it can still be informative in predicting the peak of a banking crisis. Twin crises also lead strategic complementarities between behavior of creditors and currency speculators, which can generate a "vicious circle" (Goldstein 2005). In case of the most recent episodes, we may also observe twin crises in connection with the sovereign-debt crisis in Europe.

3.3.2 Leading variables

Table 3.1: Definition of the credit-based EWIs

Description	**Abbreviation using**	
	bank credit	**total credit**
Growth of credit-to-GDP ratio (YoY)*	crb_gdp_YoYg	crt_gdp_YoYg
Change in credit-to-GDP ratio (YoY)**	crb_gdp_YoYc	crt_gdp_YoYc
Credit-to-GDP gap***	crb_gdp_gap	crt_gdp_gap
Nominal credit growth (YoY)	crb_YoY_g	crt_YoY_g
Real credit growth (YoY)	crb_r_YoY_g	crt_r_YoY_g
Real credit gap****	crb_r_gap	crt_r_gap

Notes:
*In percent; i.e. and increase of credit to GDP from 40% to 60% is a 50% growth
**In percentage points (ppts), i.e. an increase of credit to GDP from 40% to 60% is a change of 20 ppts
***Calculated as a difference between the observed credit to GDP and its trend estimated via the (one-sided, i.e. recursive) Hodrick-Prescott (HP) filter with lambda of 400,000, as recommended by the Basel Committee for activation of the countercyclical capital buffer ; in the benchmark we estimate the trend only if at least 20 consecutive quartertly observations are available
****Calculated as a percentage deviation of the observed stock of real credit from its trend estimated via the (one-sided, i.e. recursive) HP filter with lambda of 400,000; we estimate the trend only if at least 20 consecutive quartertly observations are available; the series was expressed in logarithm before estimating the trend.

Recent literature finds that a combination of credit-based and asset-price-based variables tends to provide good signaling of banking crises (Anundsen *et al.* 2016). Emerging markets have typically much less reliable data on asset prices (such as real estate prices) and other variables, so we focus only on credit-based variables, which anyway proved to be key early warning indicators in recent studies (Drehmann & Juselius 2014). Additionally, an ample empirical literature highlights credit as a powerful predictor of future distress (Schularick & Taylor (2012), Jordà *et al.* (2013), Mian *et al.* (forthcoming)). Nonetheless, we acknowledge that there might be other indicators that could potentially have a good signaling power (which we omit), but as the objective of this research is to challenge the credit-to-GDP gap as the best signaling variable, we focus only on indicators from the same area, i.e. credit markets.

We use two credit aggregates: (i) the (domestic) bank credit, and (ii) the total credit to the private sector, i.e. the sum of credit provided by domestic banks, domestic non-bank financial institutions, and by non-resident financial institutions (cross-border credit). For each of the two credit definitions, we construct the six indicators (leading to 12 variables in total) – half of which is based on the credit to GDP and an a second half is based on the credit stock (Table 3.1).

Figure 3.1 shows the average developments of the EWIs based on credit to GDP over time before and after the onset of a banking crisis, while Figure 3.2 shows those based on the credit stock. In all cases, the EWIs are usually at an elevated level before the crisis compared to after the crisis, so the question as to which variable provides the best signal needs be resolved by assessing the signals in a quantitative framework.

3.3.3 Definition of the signal

The formal framework for analysing the signals issued by the credit variables is built on the signal extraction method. Departing from the work of Kaminsky & Reinhart (1999) on EWIs, we assume two possible states of the world: crisis (D=1) and no crisis/calm times (D=0). If the leading variable (Y) exceeds the threshold θ, signal turns "on" (S=1), otherwise it remains turned "off" (S=0). Table 3.2 summarizes all four possibilities. In the upper left corner, correctly predicted crises are denoted as true positives. Analogously, correctly predicted calm times are denoted as true negatives in the lower right corner of the table. In addition, two types of errors can occur in the set up: missed crises (also labeled as Type 1 errors or false negatives) and false alarms (Type 2 errors or false positives).

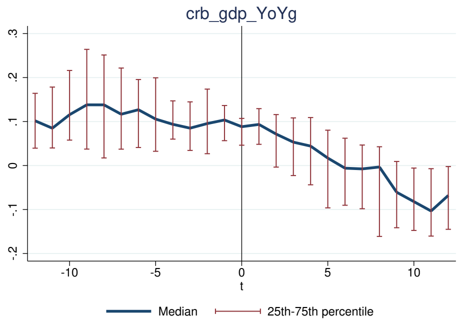
Table 3.2: Signals and crisis

		State of the world: Crisis (D=1)	State of the world: No crisis (D=0)
Signal	On (S=1)	True Positives (TP)	False Positives (FP) *Type 2 error*
Signal	Off (S=0)	False Negatives (FN) *Type 1 error*	True Negatives (TN)

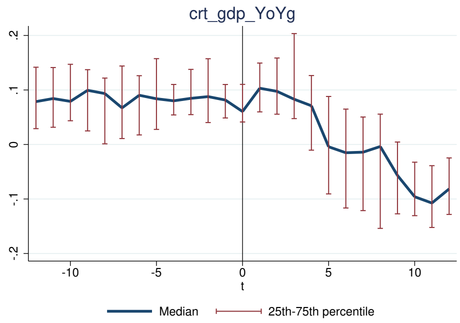
The EWI literature proposed numerous ways to analyze the signaling performance of early warning variables departing from the noise-to-signal ratio[2]

[2]Noise-to-signal ratio $= \frac{\text{Type 2 error}}{1-\text{Type 1 error}}$

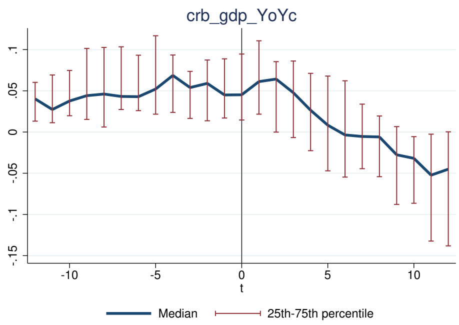
Figure 3.1: Developments of EWIs based on credit to GDP before and during banking crises



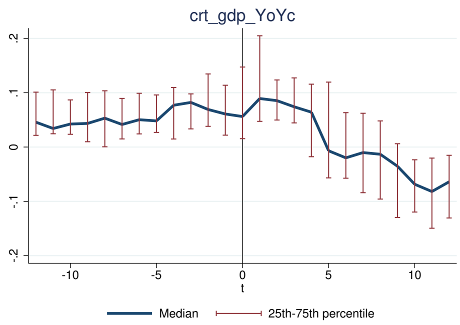
(a) Bank credit-to-GDP growth



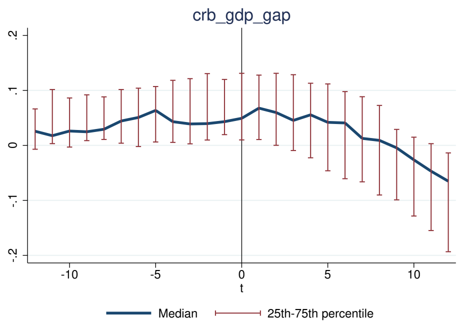
(b) Total credit-to-GDP growth



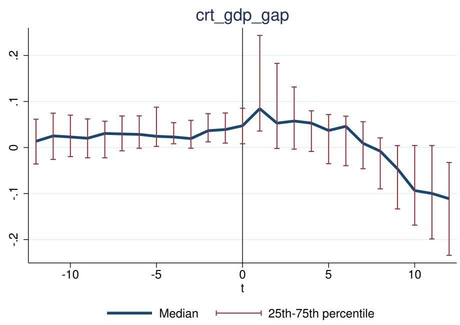
(c) Bank credit-to-GDP change



(d) Total credit-to-GDP change



(e) Bank credit-to-GDP gap



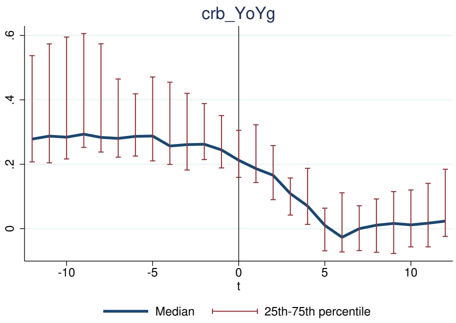
(f) Total credit-to-GDP gap

proposed by Kaminsky & Reinhart (1999). Another way to describe the trade-off is to look into the true-positives rate (TPR) and false positives rate (FPR):

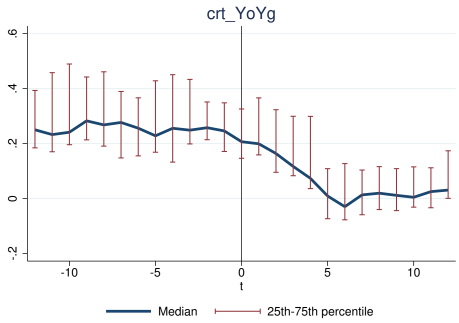
$$TPR_Y(\theta) = P(S = 1 \mid D = 1)$$
$$FPR_Y(\theta) = P(S = 1 \mid D = 0)$$

If the threshold parameter θ is set low, the signal turns "on" (S=1) easily

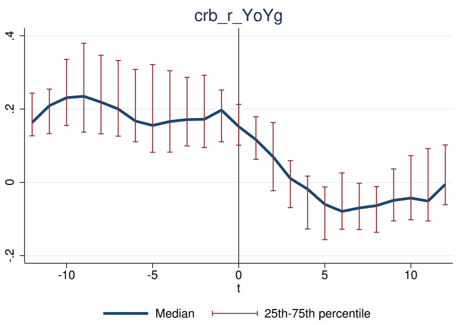
Figure 3.2: Developments of EWIs based on credit stock before and during banking crises



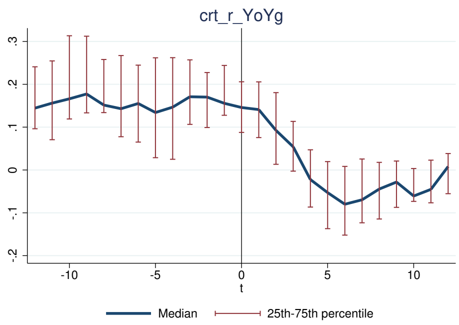
(a) Nominal bank credit growth



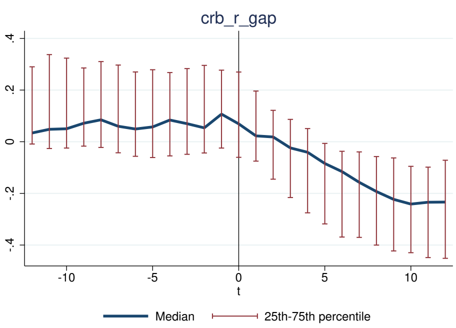
(b) Nominal total credit growth



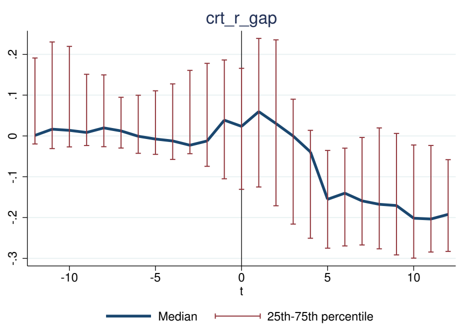
(c) Real bank credit growth



(d) Real total credit growth



(e) Real bank credit gap



(f) Real total credit gap

thus yielding high TPR but also FPR ratios. In contrast if θ is set high, the signal remains "off" (S=0) for both false alarms and true crises. This concept is also named specificity vs. sensitivity. The final outcome is therefore sensitive to the threshold parameter θ, i.e. how important are the benefits of TPR and costs of FPR for a policymaker. One approach to solve the problem is to restrict θ and model the outcome. An alternative approach is to focus on a full mapping of TPR and FPR trade-off for all possible θ by applying received operating characteristics (ROC):

$$TPR_Y(\theta) = ROC(FPR_Y(\theta))$$

The ROC curve is also a graphical tool that reveals predictive abilities of signals (Candelon *et al.* 2012). The important advantage of applying ROC is that we do not need observe the preferences of policymakers and set up a specific threshold for the signaling variable (Elliott & Lieli 2013). Furthermore, upon constructing ROC, we can compute the full area under the curve (AUC) that allows to compare the signaling properties of variables under full mapping of a threshold. More formally, the area under the ROC curve is defined as:

$$AUC = \int_{\theta=0}^{1} ROC(FPR_Y(\theta))FPR_Y'(\theta)d\theta$$

To illustrate, AUC takes value of 1 for a fully informative signal and value of 0.5 for a fully uninformative signal (e.g., toss of a coin).

3.3.4 Time horizon

To capture the crisis, we use a binary variable that takes the value of 1 if a country is in crisis, and 0 otherwise (so called "crisis window" approach). Selection of the forecasting horizon is hence crucial. Based on the latest discussion on EWIs, we follow an emerging consensus according to which a banking crisis shall be signaled at least about a year prior to its materialization to allow policymakers time to implement counter-cyclical measures (Behn *et al.* (2013), Drehmann & Juselius (2014)). At the same time the signal should not be issued far ahead of the crisis. In the analysis we therefore focus on the forecasting window of 12 to 4 quarters before the crisis, one by one. In our benchmark, we consider a 2-year (8Q) horizon (this is also in line with Drehmann & Juselius (2014)).

As the objective of this essay is to compare signaling performance of several credit-based variables, we make sure that the comparison is fair in terms of having all the indicators available in the analysis sample. In the baseline, we require at least 5 years of credit to GDP data before we calculate the credit-to-GDP gap and the real credit gap (see notes below Table 3.1). We take into account only those observations for credit growth or change/growth in credit to GDP for which the gaps also exist. In principle, we therefore omit credit growth and change indicators from the first 5 years of each country. This leads to having the same number of analyzed observations (for a given horizon) for all leading variables.

3.4 Results

In this section we present the results (in terms of the AUC) on signaling properties of the analyzed credit variables across various horizons, i.e. 12 to 4 quarters prior to the crisis observations.

Table 3.3: Signaling quality (AUC) of bank-credit based EWIs

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.637**	0.721***	0.654**	0.703***	0.628	0.588
	(0.0708)	(0.0724)	(0.0632)	(0.0660)	(0.0799)	(0.0635)
Obs.	2,001	2,001	2,001	2,001	2,001	2,001
5Q	0.645***	0.733***	0.661***	0.713***	0.644**	0.589*
	(0.0486)	(0.0500)	(0.0476)	(0.0449)	(0.0578)	(0.0485)
Obs.	1,967	1,967	1,967	1,967	1,967	1,967
6Q	0.650***	0.738***	0.657***	0.720***	0.655***	0.587**
	(0.0423)	(0.0404)	(0.0399)	(0.0367)	(0.0470)	(0.0395)
Obs.	1,933	1,933	1,933	1,933	1,933	1,933
7Q	0.654***	0.741***	0.653***	0.727***	0.664***	0.588***
	(0.0354)	(0.0354)	(0.0354)	(0.0326)	(0.0406)	(0.0336)
Obs.	1,900	1,900	1,900	1,900	1,900	1,900
8Q	0.652***	0.732***	0.646***	0.734***	0.672***	0.590***
	(0.0338)	(0.0327)	(0.0315)	(0.0284)	(0.0368)	(0.0300)
Obs.	1,867	1,867	1,867	1,867	1,867	1,867
9Q	0.656***	0.729***	0.639***	0.742***	0.683***	0.591***
	(0.0299)	(0.0300)	(0.0297)	(0.0268)	(0.0333)	(0.0281)
Obs.	1,834	1,834	1,834	1,834	1,834	1,834
10Q	0.660***	0.727***	0.631***	0.745***	0.693***	0.591***
	(0.0279)	(0.0280)	(0.0284)	(0.0236)	(0.0288)	(0.0251)
Obs.	1,801	1,801	1,801	1,801	1,801	1,801
11Q	0.658***	0.719***	0.625***	0.745***	0.696***	0.590***
	(0.0254)	(0.0261)	(0.0267)	(0.0228)	(0.0267)	(0.0248)
Obs.	1,768	1,768	1,768	1,768	1,768	1,768
12Q	0.655***	0.715***	0.620***	0.743***	0.694***	0.590***
	(0.0257)	(0.0246)	(0.0247)	(0.0210)	(0.0244)	(0.0230)
Obs.	1,735	1,735	1,735	1,735	1,735	1,735

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

We estimate non-parametric ROC curves and employ trapezoid approximation to estimate the area under the curve. Following the approach of Drehmann & Juselius (2014) and Janes *et al.* (2009), we correct for potential clustering across the country dimension and compute bootstrapped standard errors using 1000 replications. In line with the early warning literature we evaluate the performance of the indicators with respect to two criteria: strength of the signal and its stability over time. A natural benchmark against which to assess the AUC (strength of the signal) is the value of 0.5, and the significance is calculated compared to 0.5. A desirable EWI should not only issue a strong AUC but this value should also be consistent across the time span.

Table 3.4: Signaling quality (AUC) of total-credit based EWIs

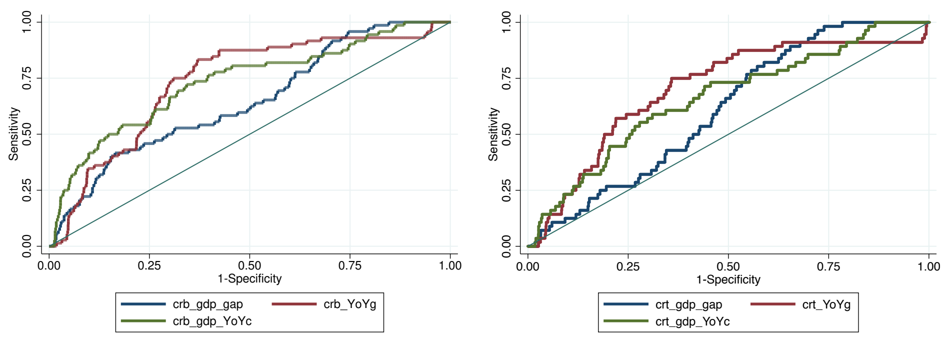
	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.621	0.679**	0.631**	0.662**	0.564	0.589
	(0.0808)	(0.0838)	(0.0512)	(0.0793)	(0.101)	(0.0645)
Obs.	1,687	1,687	1,687	1,687	1,687	1,687
5Q	0.625**	0.683***	0.626***	0.675***	0.586	0.582*
	(0.0588)	(0.0578)	(0.0420)	(0.0543)	(0.0721)	(0.0450)
Obs.	1,657	1,657	1,657	1,657	1,657	1,657
6Q	0.619**	0.676***	0.612***	0.683***	0.600*	0.577**
	(0.0490)	(0.0475)	(0.0351)	(0.0458)	(0.0580)	(0.0382)
Obs.	1,627	1,627	1,627	1,627	1,627	1,627
7Q	0.611***	0.669***	0.607***	0.690***	0.609**	0.580***
	(0.0426)	(0.0391)	(0.0342)	(0.0396)	(0.0510)	(0.0297)
Obs.	1,598	1,598	1,598	1,598	1,598	1,598
8Q	0.603***	0.656***	0.603***	0.699***	0.618***	0.587***
	(0.0388)	(0.0372)	(0.0310)	(0.0360)	(0.0448)	(0.0278)
Obs.	1,569	1,569	1,569	1,569	1,569	1,569
9Q	0.609***	0.656***	0.598***	0.710***	0.636***	0.592***
	(0.0348)	(0.0357)	(0.0287)	(0.0340)	(0.0400)	(0.0262)
Obs.	1,540	1,540	1,540	1,540	1,540	1,540
10Q	0.620***	0.658***	0.595***	0.716***	0.654***	0.597***
	(0.0333)	(0.0322)	(0.0268)	(0.0316)	(0.0374)	(0.0249)
Obs.	1,511	1,511	1,511	1,511	1,511	1,511
11Q	0.627***	0.658***	0.592***	0.721***	0.664***	0.600***
	(0.0311)	(0.0300)	(0.0254)	(0.0278)	(0.0349)	(0.0240)
Obs.	1,482	1,482	1,482	1,482	1,482	1,482
12Q	0.631***	0.659***	0.590***	0.723***	0.668***	0.603***
	(0.0290)	(0.0273)	(0.0240)	(0.0258)	(0.0312)	(0.0246)
Obs.	1,453	1,453	1,453	1,453	1,453	1,453

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Among the EWIs based on bank credit (Table 3.3, all analyzed variables have AUC significantly higher than 0.5. Change in credit to GDP (for shorter horizons of 4Q-7Q) and nominal credit growth (for longer horizons of 8Q-12Q) have the highest AUCs, outperforming the credit-to-GDP gap.

Table 3.4 shows results for EWIs based on the total credit. The AUCs for total credit are in general slightly lower than for bank credit, but still significantly higher than 0.5 for almost all cases. As a results, the usage of total credit does not improve much the signaling power over bank credit. In terms of individual EWIs, again, the change in credit to GDP (for shorter horizons of 4Q-5Q) and nominal credit growth (for longer horizons 6Q-12Q) are outperforming the credit-to-GDP gap.

Figure 3.3: ROC curves: 8Q horizon



(a) Bank credit (b) Total credit

Table 3.5: Pair-wise comparison of AUCs

	crb_YoYg	crb_gdp_YoYc		crt_YoYg	crt_gdp_YoYc
crb_gdp_gap	0.0103	0.0007	crt_gdp_gap	0.0504	0.1348
crb_YoYg		0.9326	crt_YoYg		0.3133

Reported p-values of pairwise tests.

Figure 3.3 shows the ROC curves for the two best indicators, namely the nominal credit growth and the change in credit to GDP, in comparison to the credit-to-GDP gap for the 8Q horizon for bank and total credit, respectively. Visually, the ROC curves for the best EWIs are further away from the one for the credit-to-GDP gap. We also run a pairwise statistical test of whether the differences in AUCs are statistically significant (Table 3.5). The results confirm that AUCs for credit-to-GDP gap are significantly different from AUCs for nominal credit growth and the change in credit to GDP for bank credit. In case of total credit pairwise test also rejects that same signaling properties of nominal credit growth and credit-to-GDP gap for total credit.

3.5 Robustness

3.5.1 Cumulative change in credit-to-GDP ratio

Table 3.6: Signaling quality (AUC) of the credit-to-GDP ratio changes computed over different periods

	(1) crb_gdp_YoYc[a]	(2) crb_gdp_YoYc_3Y[b]	(3) crb_gdp_YoYc_5Y[c]
4Q	0.721***	0.703***	0.722***
	(0.0724)	(0.0741)	(0.0646)
Obs.	2,001	2,001	2,001
5Q	0.733***	0.718***	0.733***
	(0.0500)	(0.0490)	(0.0473)
Obs.	1,967	1,967	1,967
6Q	0.738***	0.720***	0.728***
	(0.0404)	(0.0414)	(0.0380)
Obs.	1,933	1,933	1,933
7Q	0.741***	0.720***	0.723***
	(0.0354)	(0.0363)	(0.0350)
Obs.	1,900	1,900	1,900
8Q	0.732***	0.717***	0.717***
	(0.0327)	(0.0321)	(0.0303)
Obs.	1,867	1,867	1,867
9Q	0.729***	0.717***	0.712***
	(0.0300)	(0.0287)	(0.0282)
Obs.	1,834	1,834	1,834
10Q	0.727***	0.714***	0.707***
	(0.0280)	(0.0265)	(0.0277)
Obs.	1,801	1,801	1,801
11Q	0.719***	0.710***	0.703***
	(0.0261)	(0.0240)	(0.0256)
Obs.	1,768	1,768	1,768
12Q	0.715***	0.704***	0.702***
	(0.0246)	(0.0233)	(0.0224)
Obs.	1,735	1,735	1,735

[a]Change in credit-to-GDP ratio computed over one year (also used in the baseline).
[b]Cummulative change in credit-to-GDP ratio computed over 3 years
[c]Cummulative change in credit-to-GDP ratio computed over 5 years
Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

One of the advantages of the concept of credit-to-GDP gap is that it captures the deviation of current credit developments from its past "average" development, thus taking into account past observations. Our best EWIs, both the credit growth and the change in credit to GDP, however, only take into account the four past quarters of development. We thus construct cumulative changes in credit to GDP (over 3Y and 5Y) to check whether such indicators covering credit evolution over a longer period might have even better signaling properties. Table 3.6 shows the results for bank credit, suggesting that the cumulative change in credit to GDP are still very good EWIs, with high AUCs, but either equal or somewhat lower than the 1Y change, which we have included into our initial specification. Similar results for total credit are reported in the Appendix D.

3.5.2 Alternative calculation of the credit-to-GDP gap

One reason for the inferior performance of the credit-to-GDP gap in emerging markets could be that we do not measure the gap properly when applying a very high smoothing parameter lambda of 400,000 in estimating the trend of credit-to-GDP ratio via the Hodrick-Prescott filter. BCBS (2010) suggested that the smoothing parameter should reflect the length of the financial cycle, with lambda of 400,000 corresponding to the case when financial cycle lasts approximately four times longer than the business cycle. Available studies indicate that financial cycles in emerging markets are shorter than in advanced countries (BCBS 2010). Thus, perhaps a different (lower) smoothing parameter should be applied to estimate the trend and the gap. As a robustness check, we re-estimated the credit-to-GDP gap with lambdas of 1,600 (the same length as the business cycle), 25,000 (about twice the length of the business cycle), and 100,000 (about three times the length of the business cycle).

Table 3.7 presents the results for the bank credit-to-GDP gap and Appendix D provides the parallel evidence for total credit-to-GDP gap. The results show that applying a lower lambda does not lead to an improved signaling performance as measured by the AUC. Interestingly, the highest lambda of 400,000 works best also for emerging markets.

Table 3.7: Signaling quality (AUC) of the credit-to-GDP gaps with various lambdas

	(1) crb_gdp_gap λ=400,000	(2) crb_gdp_gap λ=100,000	(3) crb_gdp_gap λ=25,000	(4) crb_gdp_gap λ=1,600
4Q	0.654**	0.651**	0.651**	0.597
	(0.0632)	(0.0659)	(0.0627)	(0.0712)
Obs.	2,001	2,001	2,001	2,001
5Q	0.661***	0.657***	0.653***	0.616**
	(0.0476)	(0.0483)	(0.0455)	(0.0500)
Obs.	1,967	1,967	1,967	1,967
6Q	0.657***	0.652***	0.645***	0.617***
	(0.0399)	(0.0418)	(0.0393)	(0.0413)
Obs.	1,933	1,933	1,933	1,933
7Q	0.653***	0.647***	0.640***	0.620***
	(0.0354)	(0.0365)	(0.0357)	(0.0362)
Obs.	1,900	1,900	1,900	1,900
8Q	0.646***	0.640***	0.634***	0.620***
	(0.0315)	(0.0317)	(0.0319)	(0.0327)
Obs.	1,867	1,867	1,867	1,867
9Q	0.639***	0.631***	0.625***	0.619***
	(0.0297)	(0.0315)	(0.0311)	(0.0294)
Obs.	1,834	1,834	1,834	1,834
10Q	0.631***	0.623***	0.617***	0.613***
	(0.0284)	(0.0288)	(0.0281)	(0.0276)
Obs.	1,801	1,801	1,801	1,801
11Q	0.625***	0.616***	0.609***	0.607***
	(0.0267)	(0.0277)	(0.0271)	(0.0269)
Obs.	1,768	1,768	1,768	1,768
12Q	0.620***	0.611***	0.603***	0.603***
	(0.0247)	(0.0260)	(0.0257)	(0.0258)
Obs.	1,735	1,735	1,735	1,735

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

3.5.3 Alternative definition of crisis dummies

In the baseline specification, we use "crisis window", i.e. crisis dummy is equal to 1 for the full period when a country is in crisis. Alternatively, we can define the "dependent" variable as capturing only the starting quarter of the crisis. As a result, for a given horizon, the number of 1s in our sample equals the number of analyzed crises. This could be a clearer approach, as the EWIs often reach their maxima just before the crisis (say one quarter) and correctly predict a country being in crisis over a horizon of say 4 quarters (assuming a typical crisis

Table 3.8: Signaling quality (AUC) of bank-credit based EWIs (different definition of crisis dummies)

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.637**	0.721***	0.654**	0.703***	0.628	0.588
	(0.0669)	(0.0710)	(0.0622)	(0.0621)	(0.0777)	(0.0642)
Obs.	2,001	2,001	2,001	2,001	2,001	2,001
5Q	0.657**	0.747***	0.670**	0.727***	0.663*	0.593
	(0.0730)	(0.0718)	(0.0746)	(0.0666)	(0.0850)	(0.0688)
Obs.	1,951	1,951	1,951	1,951	1,951	1,951
6Q	0.662**	0.747***	0.648**	0.738***	0.682**	0.591
	(0.0707)	(0.0710)	(0.0755)	(0.0634)	(0.0839)	(0.0686)
Obs.	1,903	1,903	1,903	1,903	1,903	1,903
7Q	0.671**	0.749***	0.641*	0.753***	0.696**	0.599
	(0.0759)	(0.0687)	(0.0797)	(0.0649)	(0.0832)	(0.0690)
Obs.	1,856	1,856	1,856	1,856	1,856	1,856
8Q	0.654*	0.693**	0.619	0.766***	0.707***	0.609*
	(0.0815)	(0.0834)	(0.0737)	(0.0613)	(0.0767)	(0.0664)
Obs.	1,809	1,809	1,809	1,809	1,809	1,809
9Q	0.681**	0.716***	0.601	0.783***	0.746***	0.609*
	(0.0773)	(0.0750)	(0.0755)	(0.0646)	(0.0641)	(0.0666)
Obs.	1,762	1,762	1,762	1,762	1,762	1,762
10Q	0.691***	0.707***	0.588	0.766***	0.757***	0.606
	(0.0639)	(0.0713)	(0.0760)	(0.0599)	(0.0529)	(0.0665)
Obs.	1,715	1,715	1,715	1,715	1,715	1,715
11Q	0.653**	0.663**	0.580	0.754***	0.729***	0.601
	(0.0704)	(0.0742)	(0.0768)	(0.0534)	(0.0503)	(0.0700)
Obs.	1,668	1,668	1,668	1,668	1,668	1,668
12Q	0.650**	0.682**	0.583	0.737***	0.694***	0.607
	(0.0743)	(0.0784)	(0.0808)	(0.0500)	(0.0497)	(0.0695)
Obs.	1,621	1,621	1,621	1,621	1,621	1,621

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

lasts longer than 4 quarters). However, this would be useless for policymakers who, by observing an EWIs surpassing a threshold, would predict their country to be in crisis over a certain horizon but not be sure as to when exactly the crisis starts. Thus, in this specification, for example, for a crisis starting in 2008q3 and using the 4Q horizon, we are interested in signaling properties of various variables in the quarter exactly 4 quarters before the start of the crisis, i.e. in 2007q3. Quarters in between 2007Q3 and 2008q2 are not taken into account.

Table 3.8 shows the results. Again, change in credit-to-GDP ratio and nominal credit growth are the best EWIs , with very high EWIs, while the credit-to-GDP gap is in many cases even not significantly different from 0.5.

3.5.4 Alternative requirement for data availability to calculate credit-to-GDP gaps

Table 3.9: Signaling quality (AUC) of main bank-credit based EWIs with different sample sizes

	(1) crb_gdp_YoYc	(2) crb_gdp_gap	(3) crb_YoY_g	(4) crb_gdp_YoYc	(5) crb_gdp_gap	(6) crb_YoY_g
	3Y of obs. required to compute the gaps			10Y of obs. required to compute the gaps		
4Q	0.716***	0.660**	0.685***	0.746**	0.717***	0.793***
	(0.0725)	(0.0645)	(0.0637)	(0.0991)	(0.0844)	(0.107)
Obs.	2,203	2,203	2,203	1,394	1,394	1,394
5Q	0.711***	0.653***	0.684***	0.733***	0.733***	0.787***
	(0.0511)	(0.0478)	(0.0463)	(0.0726)	(0.0574)	(0.0760)
Obs.	2,169	2,169	2,169	1,360	1,360	1,360
6Q	0.709***	0.644***	0.686***	0.718***	0.732***	0.777***
	(0.0435)	(0.0405)	(0.0389)	(0.0611)	(0.0489)	(0.0643)
Obs.	2,135	2,135	2,135	1,326	1,326	1,326
7Q	0.709***	0.639***	0.691***	0.715***	0.733***	0.776***
	(0.0363)	(0.0387)	(0.0327)	(0.0538)	(0.0427)	(0.0566)
Obs.	2,102	2,102	2,102	1,293	1,293	1,293
8Q	0.698***	0.633***	0.697***	0.715***	0.732***	0.781***
	(0.0339)	(0.0326)	(0.0283)	(0.0488)	(0.0382)	(0.0521)
Obs.	2,069	2,069	2,069	1,260	1,260	1,260
9Q	0.695***	0.625***	0.704***	0.718***	0.731***	0.786***
	(0.0312)	(0.0305)	(0.0264)	(0.0448)	(0.0366)	(0.0474)
Obs.	2,036	2,036	2,036	1,227	1,227	1,227
10Q	0.692***	0.617***	0.706***	0.724***	0.730***	0.790***
	(0.0285)	(0.0274)	(0.0245)	(0.0396)	(0.0330)	(0.0419)
Obs.	2,003	2,003	2,003	1,194	1,194	1,194
11Q	0.684***	0.611***	0.706***	0.726***	0.729***	0.794***
	(0.0264)	(0.0265)	(0.0224)	(0.0386)	(0.0312)	(0.0403)
Obs.	1,970	1,970	1,970	1,161	1,161	1,161
12Q	0.681***	0.607***	0.706***	0.719***	0.722***	0.792***
	(0.0262)	(0.0259)	(0.0213)	(0.0350)	(0.0305)	(0.0368)
Obs.	1,937	1,937	1,937	1,128	1,128	1,128

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

In our baseline specification, we required existence of 20 quarters (5 years) before a credit-to-GDP gap is calculated. This might be too restrictive, as we omit a number of observations for which (technically) we could calculate the gap. On the other hand, for the calculation of the gap for setting the Basel III countercyclical capital buffer rate, BCBS (2010) recommends at least 20 years of data. This is largely restrictive for many emerging markets, but perhaps a somewhat higher number than 5 years of data could be considered. In this robustness check, we have calculated the credit-to-GDP gap, requiring either only 3 years of data (to have more observations) or 10 years of data (leading to less observations, but more precisely estimated gap given the large lambda applied). As in the baseline analysis, also here we fairly compare the performance of the three main bank-credit-based EWIs for the same number of observations.

Table 3.9 presents the results. Interestingly, using only 3 years of data to calculate the trend and the gap does not dramatically change the results. 10 years of data increases the AUCs of the credit-to-GDP gap above 0.7. It is still lower than the AUC for credit growth, but higher than the AUC for the change in credit to GDP (although, statistically, taking into account the standard errors, they are not significantly different, a conclusion which is also reached when using total credit data).

3.5.5 More homogeneous country groupings

In the main analysis, we focused on a wide range on 36 emerging economies. As a part of the robustness, we slice the sample in three more homogeneous regions: emerging Europe, Asia and Latin America.[3]

Table 3.10 reports results for 8Q horizon and Appendix C includes full results. Overall, AUCs for Asia and Europe are broadly in line those of the full sample, i.e. high AUCs credit growth and credit-to-GDP change.[4] Nonetheless, some heterogeneities do appear.

AUC estimates for all credit variables in emerging Europe are high. AUCs are in all specifications above 0.7 and fairly often also higher than 0.8 – magnitudes very similar advanced economies (as reported by Drehmann & Juselius (2014)).

While signaling quality of change in credit-to-GDP ratio dominates in six

[3]Europe: Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia and Ukraine. Latin America: Argentina, Brazil, Chile and Mexico. Asia: China, Hong Kong SAR, India, Indonesia, Malaysia, South Korea and Thailand.

[4]AUCs for Latin America are should be treated with caution. This is due to the very small size of the sample both in terms of analyzed countries and crisis episodes.

Table 3.10: Signaling quality (AUC) across regions: 8Q horizon

8Q	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
Europe	0.753***	0.858***	0.834***	0.802***	0.791***	0.793***
	(0.0305)	(0.0283)	(0.0278)	(0.0336)	(0.0351)	(0.0260)
Obs.	838	838	838	838	838	838
Asia	0.729***	0.755***	0.620***	0.844***	0.819***	0.548
	(0.0436)	(0.0427)	(0.0466)	(0.0279)	(0.0363)	(0.0370)
Obs.	509	509	509	509	509	509
LatAm	0.637	0.593	0.44	0.509	0.509	0.198***
	(0.111)	(0.0988)	(0.0430)	(0.127)	(0.114)	(0.0504)
Obs.	217	217	217	217	217	217

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

out of nine specifications, credit-to-GDP gap is doing reasonably well especially over the very short horizons. One possible reason for a good performance of the gap measure is that all crises episodes in the European sample occurred in 2008 – i.e. at the time when most of these economies, by their characteristics including credit dynamics, resemble advanced rather than emerging economies. It is hence not surprising that their credit-to-GDP gaps (which are now quantitatively similar to advanced economies) also yield signaling results (AUCc) closer to the ones observed for advanced economies. By 2008, there is also a sufficient existence of credit data to compute more reliable deviation from the long-term trend which is generally the main challenge in the emerging markets and also the motivation for this essay. We also perform the test of equality of ROC curves for credit-to-GDP gap, credit-to-GDP ratio growth and nominal credit growth and the results confirm that the difference across the AUCs is not statistically significant.

This result is particularly interesting as it bridges our findings from the main text on EMEs with those on advanced economies. Nominal credit growth and the change in credit-to-GDP ratio still remain to have very high signaling properties (in line with the findings from our EME analysis) while credit-to-GDP starts also to be of a similar significance (conclusion from parallel AE studies).

3.5.6 Alternative crisis database

As has been noted, definition of the banking crisis can play a big role in driving the results. To address these concerns, we also re-run our analysis against an alternative data source. In this section we report the results using crisis database of Babecký *et al.* (2014)[5] Babecký *et al.* (2014) incorporated a finer definition of crisis, using extensive literature overview as well as expert judgment to compile the date. The concern, however, is that the data is only reported on a more advanced sub-set of our EME sample.[6]

Table 3.11 shows the results. The broad conclusion from the analysis remain robust as nominal credit growth is the best EWI in all specifications.

Table 3.11: Signaling quality (AUC) of bank-credit based EWIs: Alternative crisis database

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.460	0.609	0.649	0.650	0.491	0.567
	(0.152)	(0.170)	(0.142)	(0.113)	(0.164)	(0.0817)
Obs.	536	536	536	536	536	536
5Q	0.472	0.617	0.655	0.675**	0.506	0.589
	(0.102)	(0.112)	(0.0934)	(0.0718)	(0.104)	(0.0560)
Obs.	536	536	536	536	536	536
6Q	0.488	0.613	0.655**	0.698***	0.540	0.600**
	(0.0853)	(0.0955)	(0.0783)	(0.0560)	(0.0814)	(0.0483)
Obs.	536	536	536	536	536	536
7Q	0.520	0.628*	0.663**	0.715***	0.585	0.614***
	(0.0710)	(0.0805)	(0.0633)	(0.0459)	(0.0597)	(0.0420)
Obs.	536	536	536	536	536	536
8Q	0.545	0.645**	0.666***	0.722***	0.610**	0.621***
	(0.0604)	(0.0649)	(0.0554)	(0.0442)	(0.0552)	(0.0383)
Obs.	536	536	536	536	536	536
9Q	0.571	0.663***	0.672***	0.727***	0.622**	0.628***
	(0.0536)	(0.0547)	(0.0521)	(0.0392)	(0.0478)	(0.0380)
Obs.	536	536	536	536	536	536
10Q	0.589*	0.674***	0.673***	0.725***	0.630***	0.629***
	(0.0498)	(0.0486)	(0.0427)	(0.0389)	(0.0431)	(0.0331)
Obs.	536	536	536	536	536	536
11Q	0.601**	0.682***	0.671***	0.721***	0.635***	0.628***
	(0.0448)	(0.0435)	(0.0413)	(0.0374)	(0.0412)	(0.0309)
Obs.	536	536	536	536	536	536
12Q	0.607**	0.683***	0.664***	0.718***	0.635***	0.626***
	(0.0421)	(0.0404)	(0.0375)	(0.0356)	(0.0369)	(0.0304)
Obs.	536	536	536	536	536	536

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

[5]We report the results on the sample where at least two of the sources claims that a crisis occurred.

[6]Bulgaria, Chile, the Czech Republic, Estonia, Hungary, Israel, Korea, Latvia, Lithuania, Mexico, Poland, Romania, Slovakia, Slovenia and Turkey.

3.5.7 Summary of results

The overall results of our analysis including all robustness checks can be summarized as follows. First, all analyzed credit variables for both bank and total credit do have reasonable signallng properties with AUC (in most specifications significantly) above 0.5 and yield consistent signals over time. However, the AUC levels of the best EWIs are in general lower than for the best EWIs reported in Drehmann & Juselius (2014) for advanced economies. This is true especially for the credit-to-GDP gap indicators, for which they report values above 0.8, while in our case the AUC of these EWIs lies below 0.7. Drehmann & Tsatsaronis (2014) report similarly low AUC for credit-to-GDP gap for emerging market (around 0.6-0.7), which is in line with our findings.

Second, nominal credit growth and change in credit to GDP in general outperform the credit-to-GDP gap indicators, for most horizons significantly, and this holds for both bank and total credit. This is yet another confirmation that the credit-to-GDP gap does not work that well as in advanced economies, a point raised earlier by Geršl & Seidler (2015) as well as others. Thus, emerging market can do sufficiently well with building their early warning system around the credit growth and the change in credit to GDP, without a need to discuss the estimation of the trend via various filtering techniques.

The only cases in which credit-to-GDP gap starts to work properly (with AUCs above 0.7 and not significantly different from the one for the nominal credit growth) are specifications with sufficiently long time series of credit to GDP (about 10 years and more) or if we strictly focus only on the latest trends in emerging Europe. This is in line with the BCBS (2010) Basel III guidance that for a proper credit-to-GDP gap calculation, a country should have a long time series (at least 20 years of quarterly data) to compute deviation from the long-run trend. Additionally, results on emerging Europe highlight both very good signaling properties of two best-performing EME indicators (nominal credit growth and change in credit to GDP) and credit-to-GDP gap. This finding hence bridges the established results on advanced economies with our findings documented when strictly looking into the EMEs.

Third, the analysis shows that bank-credit-based indicators perform better than total-credit-based indicators. This is a novel finding as in general, total credit should better capture the degree of leverage in the private sector (especially in the corporate sector), as it includes not only bank loans, but also bonds issues, cross-border funding and domestic non-bank sources of finance such as leasing or loans provided my non-bank providers. On one hand, in emerging markets, non-bank sources of financing are usually of lower importance than in advanced markets due to underdeveloped financial markets. On the other hand, some of the funding sources (especially domestic non-bank financial institutions such as leasing companies or direct cross-border credit for bigger firms) do play a vital role in the sample countries. As we focus on banking crises, perhaps it is mainly the excessive bank credit provision than anything else that leads to the boom and busts type of financial cycles. In any case, this "puzzle" requires follow-up research.

3.6 Conclusions

This paper contributes to the existing literature on early warning indicators as well as to the discussion on the appropriateness of credit-to-GDP gap as a leading variable for any country for activation of the countercyclical capital buffer instrument in Basel III. We analyzed the performance of six alternative credit-based variables in signaling banking distress in the context of emerging markets, both for bank and total credit.

We used the BIS data on total credit to the private sector as well as data from national sources for the period of 1987–2015 and focused on the development of the credit variables prior to banking crises. The analysis was performed by employing the receiver operating characteristics (ROC) curve and the area under the curve (AUC). This method provides a practical way to compare and evaluate different variables without the need to specify a threshold value for the indicators. By providing a full mapping of the ROC curve and computing AUC, the method does not need to address the problem of unknown preferences of the policymakers.

Our results show that nominal credit growth and the change in credit-to-GDP ratio have the best signaling properties and significantly outperform the credit-to-GDP gap in almost all specifications for policy-relevant longer horizons, with the exception of the case in which we require a sufficiently long time series before the gap is calculated (at least 10 years). This finding is in stark contrast with the results on advanced economies where the credit-to-GDP gap significantly outperforms other credit and also non-credit variables. We also found that bank credit variables outperform total credit variables in emerging markets. The results emphasize the importance of caution when applying statistical methods calibrated for advanced markets to emerging economies.

However, the signaling strength of the credit growth variables seems to be lower than the strength of the best-performing variable for advanced economies. This calls for further research on driving forces of banking crises in emerging markets and probably for a multivariate approach to early warning systems.

Appendix A: Data availability

Table 3.12: Starting dates of the data availability

Country		Credit	
Name	**Code**	**Bank**	**Total**
Albania	AL	1995q1	NA
Argentina	AR	1987q1	1987q1
Armenia	AM	2000q1	NA
Belarus	BT	1999q4	1999q4
Bosnia and Herzegovina	BA	1997q3	1997q3
Brazil	BR	1993q4	1993q4
Bulgaria	BG	1997q4	1999q1
Chile	CL	1998q1	1987q1
China	CN	1987q1	1987q1
Croatia	HR	1995q1	1995q1
Czech Republic	CZ	1993q1	1993q1
Estonia	EE	1995q1	2003q4
Georgia	GE	2003q1	2003q1
Hong Kong	HK	1987q1	1987q1
Hungary	HU	1989q4	1989q4
India	IN	1987q1	1987q1
Indonesia	ID	1987q1	1987q1
Israel	IL	1987q1	1987q1
Latvia	LV	1995q1	2004q1
Lithuania	LT	1995q1	2004q1
Macedonia	MK	1995q1	2004q4
Malaysia	MY	1987q1	1987q1
Mexico	MX	1987q1	1987q1
Moldova	MD	2000q4	2000q4
Montenegro	ME	2002q4	NA
Poland	PL	1992q1	1992q1
Romania	RO	1996q4	1998q4
Russia	RU	1995q2	1995q2
Serbia	RS	2002q1	NA
Slovakia	SK	1995q1	2004q1
Slovenia	SL	1995q1	2001q4
South Africa	ZA	1987q1	1987q1
South Korea	KR	1987q1	1987q1
Thailand	TH	1987q1	1987q1
Turkey	TR	1987q1	1987q1
Ukraine	UA	1995q4	2008q4

Source: BIS, national data

Appendix B: List of banking crises

Table 3.13: List of crises covered in the main analysis

Country code	Crisis Start	Crisis End	Crisis Covered
AL	1994q1	1994q4	
AM	1994q1	1994q4	
AR	1989q4	1991q4	
AR	1995q1	1995q4	X
AR	2001q4	2003q4	X
BA	1992q1	1996q4	
BG	1994q1	1997q4	
BR	1990q1	1990q4	
BR	1994q4	1998q4	
BY	1995q1	1995q4	
CN	1998q1	1998q4	X
CL	1981q1	1985q4	
CZ	1996q2	1999q4	
EE	1992q4	1994q4	
EE	1998q1	1999q4	
GE	1991q1	1995q4	
HR	1998q1	1999q4	
HU	1991q1	1995q4	
HU	2008q3	2009q4	X
IL	1977q1	1985q4	
IN	1993q1	1993q4	X
ID	1997q4	2001q4	X
KR	1997q3	1998q4	X
LV	1995q2	1998q4	
LV	2008q3	2012q4	X
LT	1995q4	1996q4	
LT	2008q3	2009q4	X
MK	1993q1	1995q4	
MY	1997q3	1999q4	X
MX	1981q1	1985q4	
MX	1994q4	1996q4	X
PL	1992q1	1994q4	
RO	1990q1	1992q4	
RU	1998q3	1999q4	
RU	2008q3	2009q4	X
SK	1998q1	2002q4	
SI	1992q1	1992q4	
SI	2008q3	2013q4	X
TH	1983q1	1983q4	
TH	1997q3	2000q4	X
TR	2000q4	2001q4	X
UA	1998q3	1999q4	
UA	2008q1	2015q4	X

Source: Laeven & Valencia (2012), national data

Appendix C: More homogenous sub-samples

Table 3.14: Emerging Europe

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.724***	0.855***	0.872***	0.801***	0.775***	0.800***
	(0.0861)	(0.0666)	(0.0337)	(0.0815)	(0.0896)	(0.0534)
Obs.	908	908	908	908	908	908
5Q	0.729***	0.845***	0.870***	0.800***	0.774***	0.805***
	(0.0591)	(0.0533)	(0.0260)	(0.0570)	(0.0624)	(0.0346)
Obs.	890	890	890	890	890	890
6Q	0.735***	0.849***	0.857***	0.796***	0.776***	0.800***
	(0.0453)	(0.0401)	(0.0255)	(0.0460)	(0.0520)	(0.0287)
Obs.	872	872	872	872	872	872
7Q	0.743***	0.853***	0.847***	0.796***	0.782***	0.798***
	(0.0360)	(0.0338)	(0.0263)	(0.0392)	(0.0404)	(0.0270)
Obs.	855	855	855	855	855	855
8Q	0.753***	0.858***	0.834***	0.802***	0.791***	0.793***
	(0.0305)	(0.0283)	(0.0278)	(0.0336)	(0.0351)	(0.0260)
Obs.	838	838	838	838	838	838
9Q	0.760***	0.860***	0.824***	0.807***	0.799***	0.790***
	(0.0271)	(0.0268)	(0.0272)	(0.0315)	(0.0305)	(0.0253)
Obs.	821	821	821	821	821	821
10Q	0.755***	0.851***	0.810***	0.803***	0.797***	0.785***
	(0.0258)	(0.0255)	(0.0284)	(0.0285)	(0.0297)	(0.0245)
Obs.	804	804	804	804	804	804
11Q	0.739***	0.831***	0.795***	0.795***	0.789***	0.778***
	(0.0262)	(0.0289)	(0.0282)	(0.0275)	(0.0266)	(0.0238)
Obs.	787	787	787	787	787	787
12Q	0.721***	0.812***	0.777***	0.783***	0.777***	0.769***
	(0.0266)	(0.0288)	(0.0303)	(0.0262)	(0.0263)	(0.0246)
Obs.	770	770	770	770	770	770

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Table 3.15: Emerging Asia

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.705	0.744**	0.634*	0.758***	0.716**	0.538
	(0.128)	(0.111)	(0.0830)	(0.1000)	(0.140)	(0.0937)
Obs.	537	537	537	537	537	537
5Q	0.738***	0.767***	0.640**	0.792***	0.768**	0.545
	(0.0753)	(0.0668)	(0.0625)	(0.0549)	(0.0784)	(0.0622)
Obs.	530	530	530	530	530	530
6Q	0.752***	0.781***	0.634**	0.820***	0.799***	0.546
	(0.0570)	(0.0489)	(0.0577)	(0.0400)	(0.0572)	(0.0497)
Obs.	523	523	523	523	523	523
7Q	0.750***	0.780***	0.631**	0.837***	0.815***	0.549
	(0.0466)	(0.0400)	(0.0519)	(0.0328)	(0.0447)	(0.0426)
Obs.	516	516	516	516	516	516
8Q	0.729***	0.755***	0.620***	0.844***	0.819***	0.548
	(0.0436)	(0.0427)	(0.0466)	(0.0279)	(0.0363)	(0.0370)
Obs.	509	509	509	509	509	509
9Q	0.720***	0.743***	0.611***	0.855***	0.826***	0.549
	(0.0418)	(0.0404)	(0.0435)	(0.0251)	(0.0340)	(0.0347)
Obs.	502	502	502	502	502	502
10Q	0.709***	0.733***	0.600**	0.859***	0.823***	0.543
	(0.0426)	(0.0414)	(0.0394)	(0.0227)	(0.0311)	(0.0329)
Obs.	495	495	495	495	495	495
11Q	0.697***	0.723***	0.595**	0.858***	0.813***	0.538
	(0.0405)	(0.0401)	(0.0371)	(0.0215)	(0.0303)	(0.0301)
Obs.	488	488	488	488	488	488
12Q	0.695***	0.721***	0.593**	0.861***	0.804***	0.534
	(0.0423)	(0.0387)	(0.0367)	(0.0211)	(0.0314)	(0.0291)
Obs.	481	481	481	481	481	481

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Table 3.16: Latin America

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.641	0.571	0.420	0.530	0.493	0.313
	(0.238)	(0.199)	(0.0830)	(0.225)	(0.193)	(0.179)
Obs.	233	233	233	233	233	233
5Q	0.606	0.547	0.408	0.506	0.481	0.243**
	(0.183)	(0.164)	(0.0627)	(0.184)	(0.162)	(0.108)
Obs.	229	229	229	229	229	229
6Q	0.604	0.550	0.412*	0.501	0.484	0.214***
	(0.152)	(0.135)	(0.0518)	(0.162)	(0.140)	(0.0833)
Obs.	225	225	225	225	225	225
7Q	0.619	0.572	0.421*	0.505	0.496	0.201***
	(0.127)	(0.115)	(0.0450)	(0.142)	(0.134)	(0.0605)
Obs.	221	221	221	221	221	221
8Q	0.637	0.593	0.440	0.509	0.509	0.198***
	(0.111)	(0.0988)	(0.0430)	(0.127)	(0.114)	(0.0504)
Obs.	217	217	217	217	217	217
9Q	0.665*	0.624	0.454	0.517	0.525	0.197***
	(0.0950)	(0.0905)	(0.0422)	(0.124)	(0.108)	(0.0455)
Obs.	213	213	213	213	213	213
10Q	0.691**	0.649*	0.470	0.526	0.544	0.200***
	(0.0873)	(0.0810)	(0.0393)	(0.111)	(0.102)	(0.0424)
Obs.	209	209	209	209	209	209
11Q	0.714***	0.669**	0.480	0.540	0.567	0.202***
	(0.0783)	(0.0739)	(0.0379)	(0.102)	(0.0953)	(0.0388)
Obs.	205	205	205	205	205	205
12Q	0.722***	0.676***	0.492	0.534	0.571	0.213***
	(0.0731)	(0.0683)	(0.0392)	(0.0982)	(0.0891)	(0.0388)
Obs.	201	201	201	201	201	201

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Appendix D: Robustness for total credit variables

Table 3.17: Signalling quality (AUC) of the total credit-to-GDP ratio changes computed over different periods

	(1) crb_gdp_YoYc[a]	(2) crb_gdp_YoYc_3Y[b]	(3) crb_gdp_YoYc_5Y[c]
4Q	0.679**	0.643*	0.678**
	(0.0838)	(0.0835)	(0.0724)
Obs.	1,687	1,687	1,687
5Q	0.683***	0.666***	0.688***
	(0.0578)	(0.0563)	(0.0515)
Obs.	1,657	1,657	1,657
6Q	0.676***	0.668***	0.679***
	(0.0475)	(0.0474)	(0.0426)
Obs.	1,627	1,627	1,627
7Q	0.669***	0.668***	0.674***
	(0.0391)	(0.0405)	(0.0358)
Obs.	1,598	1,598	1,598
8Q	0.656***	0.660***	0.666***
	(0.0372)	(0.0356)	(0.0342)
Obs.	1,569	1,569	1,569
9Q	0.656***	0.660***	0.661***
	(0.0357)	(0.0324)	(0.0315)
Obs.	1,540	1,540	1,540
10Q	0.658***	0.659***	0.657***
	(0.0322)	(0.0298)	(0.0292)
Obs.	1,511	1,511	1,511
11Q	0.658***	0.656***	0.656***
	(0.0300)	(0.0272)	(0.0278)
Obs.	1,482	1,482	1,482
12Q	0.659***	0.650***	0.657***
	(0.0273)	(0.0267)	(0.0256)
Obs.	1,453	1,453	1,453

[a]Change in credit-to-GDP ratio computed over one year (also used in the baseline).

[b]Cummulative change in credit-to-GDP ratio computed over 3 years

[c]Cummulative change in credit-to-GDP ratio computed over 5 years

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Table 3.18: Signalling quality (AUC) of the total credit-to-GDP gaps with various lambdas

	(1) crb_gdp_gap λ=400,000	(2) crb_gdp_gap λ=100,000	(3) crb_gdp_gap λ=25,000	(4) crb_gdp_gap λ=1,600
4Q	0.631**	0.614**	0.606*	0.635*
	(0.0512)	(0.0567)	(0.0552)	(0.0794)
Obs.	1,687	1,687	1,687	1,687
5Q	0.626***	0.608**	0.595**	0.615**
	(0.0420)	(0.0450)	(0.0459)	(0.0548)
Obs.	1,657	1,657	1,657	1,657
6Q	0.612***	0.592**	0.574**	0.578*
	(0.0351)	(0.0362)	(0.0373)	(0.0466)
Obs.	1,627	1,627	1,627	1,627
7Q	0.607***	0.587**	0.566**	0.563
	(0.0342)	(0.0344)	(0.0349)	(0.0409)
Obs.	1,598	1,598	1,598	1,598
8Q	0.603***	0.582***	0.561*	0.557
	(0.0310)	(0.0315)	(0.0322)	(0.0379)
Obs.	1,569	1,569	1,569	1,569
9Q	0.598***	0.577***	0.556*	0.555
	(0.0287)	(0.0283)	(0.0285)	(0.0342)
Obs.	1,540	1,540	1,540	1,540
10Q	0.595***	0.573***	0.551*	0.551*
	(0.0268)	(0.0281)	(0.0277)	(0.0308)
Obs.	1,511	1,511	1,511	1,511
11Q	0.592***	0.570***	0.548*	0.550*
	(0.0254)	(0.0268)	(0.0253)	(0.0297)
Obs.	1,482	1,482	1,482	1,482
12Q	0.590***	0.568***	0.545*	0.550*
	(0.0240)	(0.0260)	(0.0266)	(0.0270)
Obs.	1,453	1,453	1,453	1,453

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Table 3.19: Signalling quality (AUC) of total-credit based EWIs (different definition of crisis dummies)

	(1) crb_gdp_YoYg	(2) crb_gdp_YoYc	(3) crb_gdp_gap	(4) crb_YoY_g	(5) crb_r_YoY_g	(6) crb_r_gap
4Q	0.629*	0.699***	0.596*	0.673**	0.602	0.573
	(0.0708)	(0.0781)	(0.0532)	(0.0697)	(0.0902)	(0.0570)
Obs.	1,872	1,872	1,872	1,872	1,872	1,872
5Q	0.604	0.672**	0.562	0.674**	0.608	0.542
	(0.0784)	(0.0777)	(0.0638)	(0.0787)	(0.0957)	(0.0565)
Obs.	1,827	1,827	1,827	1,827	1,827	1,827
6Q	0.593	0.654*	0.541	0.686**	0.625	0.539
	(0.0879)	(0.0805)	(0.0595)	(0.0728)	(0.0982)	(0.0528)
Obs.	1,783	1,783	1,783	1,783	1,783	1,783
7Q	0.537	0.597	0.568	0.658**	0.574	0.565
	(0.0855)	(0.0868)	(0.0756)	(0.0788)	(0.103)	(0.0599)
Obs.	1,740	1,740	1,740	1,740	1,740	1,740
8Q	0.540	0.582	0.572	0.682**	0.603	0.598*
	(0.0891)	(0.0913)	(0.0687)	(0.0765)	(0.0923)	(0.0588)
Obs.	1,699	1,699	1,699	1,699	1,699	1,699
9Q	0.604	0.633	0.558	0.705***	0.667**	0.601*
	(0.0792)	(0.0847)	(0.0657)	(0.0752)	(0.0816)	(0.0587)
Obs.	1,658	1,658	1,658	1,658	1,658	1,658
10Q	0.634*	0.636*	0.552	0.690***	0.689***	0.601
	(0.0744)	(0.0735)	(0.0739)	(0.0689)	(0.0733)	(0.0667)
Obs.	1,617	1,617	1,617	1,617	1,617	1,617
11Q	0.636*	0.624	0.559	0.695***	0.688***	0.604
	(0.0766)	(0.0752)	(0.0767)	(0.0649)	(0.0634)	(0.0708)
Obs.	1,576	1,576	1,576	1,576	1,576	1,576
12Q	0.657**	0.646**	0.558	0.698***	0.678***	0.610
	(0.0695)	(0.0769)	(0.0704)	(0.0563)	(0.0575)	(0.0697)
Obs.	1,535	1,535	1,535	1,535	1,535	1,535

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Table 3.20: Signalling quality (AUC) of main total-credit based EWIs with different sample sizes

	(1) crb_gdp_YoYc	(2) crb_gdp_gap	(3) crb_YoY_g	(4) crb_gdp_YoYc	(5) crb_gdp_gap	(6) crb_YoY_g
	3Y of obs. required to compute the gaps			10Y of obs. required to compute the gaps		
4Q	0.699***	0.596*	0.673**	0.625	0.645	0.688
	(0.0793)	(0.0543)	(0.0701)	(0.163)	(0.107)	(0.189)
Obs.	1,872	1,872	1,872	1,204	1,204	1,204
5Q	0.686***	0.579*	0.673***	0.579	0.665**	0.653
	(0.0537)	(0.0432)	(0.0505)	(0.113)	(0.0703)	(0.138)
Obs.	1,842	1,842	1,842	1,174	1,174	1,174
6Q	0.676***	0.567*	0.677***	0.541	0.659***	0.646
	(0.0432)	(0.0349)	(0.0419)	(0.0875)	(0.0570)	(0.113)
Obs.	1,812	1,812	1,812	1,144	1,144	1,144
7Q	0.659***	0.567**	0.671***	0.524	0.663***	0.645
	(0.0395)	(0.0310)	(0.0372)	(0.0782)	(0.0503)	(0.101)
Obs.	1,783	1,783	1,783	1,115	1,115	1,115
8Q	0.645***	0.568**	0.672***	0.521	0.665***	0.653*
	(0.0346)	(0.0292)	(0.0325)	(0.0654)	(0.0424)	(0.0876)
Obs.	1,754	1,754	1,754	1,087	1,087	1,087
9Q	0.644***	0.566**	0.676***	0.535	0.668***	0.662**
	(0.0331)	(0.0270)	(0.0304)	(0.0591)	(0.0384)	(0.0784)
Obs.	1,725	1,725	1,725	1,059	1,059	1,059
10Q	0.643***	0.564**	0.678***	0.559	0.677***	0.671**
	(0.0311)	(0.0269)	(0.0278)	(0.0522)	(0.0385)	(0.0740)
Obs.	1,696	1,696	1,696	1,031	1,031	1,031
11Q	0.642***	0.564***	0.679***	0.576	0.686***	0.684***
	(0.0288)	(0.0243)	(0.0256)	(0.0467)	(0.0336)	(0.0665)
Obs.	1,667	1,667	1,667	1,005	1,005	1,005
12Q	0.643***	0.563***	0.680***	0.593**	0.695***	0.697***
	(0.0271)	(0.0224)	(0.0244)	(0.0432)	(0.0317)	(0.0583)
Obs.	1,638	1,638	1,638	980	980	980

Bootstrapped standard errors in parentheses; ***,**,* indicate significance of the AUC being different from 0.5 (uninformative signal) at 1%, 5% and 10% levels, respectively.

Chapter 4

Exchange rate pass-through: What has changed since the crisis?

This essay studies how exchange rate pass-through to CPI inflation has changed since the global financial crisis. We have three main findings. First, exchange rate pass-through in emerging economies decreased after the financial crisis, while exchange rate pass-through in advanced economies has remained relatively low and stable over time. Second, we show that the declining pass-through in emerging markets is related to declining inflation. Third, we show that it is important to control for non-linearities when estimating exchange rate pass-through. These results hold for both short-run and long-run pass-through and remain robust to extensive changes in the specifications.

4.1 Introduction

Exchange rate pass-through is again at the centre of economic policy and central bank thinking (Forbes (2014) and Forbes (2015)). We have to understand how the observed large exchange rate movements translate to consumer price inflation, especially as inflation remains well below central bank targets in many advanced economies. From the perspective of some emerging market economies (EMEs) another question arises on how large exchange rate movements affect

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inflation, especially when it is already above target. In addition, as Plantin & Shin (2016) find, exchange rate pass-through can affect the financial risk-taking channel of monetary policy.

In this essay we aim to provide an overall picture of how exchange rate pass-through has evolved for both advanced and emerging market economies. We find that exchange rate pass-through in emerging economies on average decreased after the financial crisis, and that this decline in pass-through is linked to declining inflation. By contrast, in advanced economies, where inflation has tended to be consistently low, exchange rate pass-through has also remained low. Yet, in spite of the recent decline in emerging economies, pass-through estimates are still lower in advanced than in emerging economies. The results are consistent with the implications of the menu cost theory of price setting: when inflation is higher, exchange rate changes are passed through more quickly and to a larger extent because firms have to adjust prices frequently anyway (see further Taylor (2000) for a sticky price setup).

We also confirm that the results hold robustly. The pattern of declining pass-through in EMEs and low pass-through in advanced economies holds similarly for contemporaneous (quarterly), yearly and long-run pass-through estimates. This pattern also does not depend on the length of rolling window estimates: 3, 4, 5, 6 and 8-year rolling windows all show the same pattern. The results are also not dependent on the econometric methodology: while our main methodology uses an Plantin & Shin (2016) and Blundell & Bond (1998) type of system GMM panel estimates, the pattern remains under difference GMM and within group estimators. While we control for time fixed effects to ensure that common global shocks do not affect the estimates, the results also hold when dropping these fixed effects and explicitly controlling for the global business cycle or oil prices.

We also find that controlling for non-linear effects of exchange rate movements can be crucial when estimating exchange rate pass-through: as one would expect based on the menu cost theory, larger exchange rate movements have a stronger chance to overcome the menu cost of price changes and thereby are more likely to be passed-through to consumer prices. Hence, naïve linear estimates of pass-through would show an increase in emerging markets after the taper tantrum when exchange rate volatility increased sharply. However, we show that this increase disappears when one properly controls for non-linearities.

The contribution of this essay to the literature is threefold. First, we document the overall pattern of more than 20 years of exchange rate pass-through development for a large group of economies. We report that the pass-through has been low and stable in advanced economies, and higher but declining in emerging economies. The advanced economy results extends the link found earlier, for instance, by Engel (2002) and Devereux & Yetman (2008), between low pass-through and low-inflation in advanced economies in the post-crisis dataset. As for the EMEs, our results on declining pass-through extend the earlier finding in Mihaljek & Klau (2008), Aleem & Lahiani (2014) and Lopez-Villavicencio *et al.* (2016) to a more recent period and/or to a larger set of economies. Our finding of a recent decline in linear pass-through slightly contrasts with De Gregorio (2016), who finds that pass-through for large depreciations in the 2008–2015 period was lower than in the 1970s but comparable to the 1990s.[1] These results might be reconciled by the fact that we consider linear pass-through when controlling for non-linearities, while De Gregorio (2016) considers the full effects of large depreciations.

Second, we provide solid empirical evidence for a causal link between lower inflation and lower pass-through in emerging market data, as was proposed in Calvo & Reinhart (2002) and Choudhri & Hakura (2006). Our results can also be seen as extending the analysis of the low inflation - low pass-through link from advanced economies in the 1990s of Takhtamanova (2010) to emerging markets in the 2000s.

Third, we provide evidence that larger exchange rate movements lead to disproportionally larger price changes. Therefore, it is useful to control for non-linearities when estimating pass-through, especially when exchange rate volatility is changing in the sample period. One crucial example is the post taper-tantrum period when exchange rate volatility increased - and the inclusion of such periods in a naive linear setup can misleadingly suggest an increase in pass-through. This result confirms the findings in Bussière (2013), Ben Cheikh & Rault (2015) and Alvarez *et al.* (2016) of the relevance of non-linearity and provides additional support to control for non-linearities to exclude the possibility that linear pass-through estimates pick up changes in exchange rate volatility. This result is also consistent with evidence in Kohlscheen (2010) and Campa & Goldberg (2005) that pass-through to consumer prices and import prices, respectively, is higher for countries with greater nominal exchange rate

[1] Importantly, we do not exclude the possibility that the link between lower pass-through and lower inflation works through more credible monetary policy, as Gagnon & Ihrig (2004) and Bailliu & Fujii (2004) argued for advanced economies.

volatilities.

Furthermore, the results also have policy relevance when thinking about changing global conditions for monetary and economic policy setting. The average low pass-through levels today imply that central banks in general should have less “fear of floating”, at least from an inflation perspective. Yet, the lower pass-through in emerging markets also implies that the exchange rate channel of monetary policy might be less effective to affect inflation than before the financial crisis. Finally, the results further reinforce the importance of price stability by showing that lower inflation also reduces pass-through. In fact, there might be a positive feedback loop: lower pass-through could in turn further contribute to price stability.

However, the results should be read with appropriate caveats. Importantly, our results apply only for groups of countries, and not for individual economies. Hence, our results do not offer direct implications for individual countries Furthermore, our setup is necessarily limited to macroeconomic factors and only captures time invariant microeconomic factors, such as pricing power, through country fixed effects. Finally, our approach does not distinguish between exogenous and endogenous exchange rate shocks - and this distinction might matter as Forbes *et al.* (2015) and Shambaugh (2008) show. However, we mitigate this problem by consistently controlling for global shocks through time fixed effects. The remainder of the essay is organised as follows. Section 4.2 introduces the data. Section 4.3 outlines the method and discusses the results. Section 4.4 presents robustness checks. Finally, section 4.5 concludes.

4.2 Data

We analyse quarterly time-series data for 22 emerging[2] and 11 advanced[3] economies over the period 1994 Q1 – 2015 Q4.

We focus on exchange rate pass-through (ERPT) to consumer price inflation. To do so, we use log differences in quarterly seasonally adjusted consumer price indices (CPI) as our dependent variable.

We use several explanatory variables. The exchange rate series are chosen as the BIS nominal effective exchange rate (NEER) broad indices available from

[2] Argentina, Brazil, Chile, China, Colombia, the Czech Republic, Hong Kong SAR, Hungary, India, Indonesia, Israel, Korea, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, Singapore, South Africa, Thailand and Turkey.

[3] Australia, Canada, Denmark, the euro area, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States.

1994 with 2010 as the indices' base year. In the regression analysis we use log differences in the average quarterly NEER indices. In our definition, an increase in the NEER implies an appreciation of the local exchange rate. Later, we also use log differences in average quarterly bilateral US dollar exchange rates. We also control for the business cycle by including measures of the output gap. The underlying real GDP series are taken from national sources. The output gap is calculated by employing the standard univariate Hodrick-Prescott filtering method with the smoothing parameter λ set to 1600 for all available quarterly GDP data. For the analysis, we use the data starting in 1994 Q1 or later depending on their availability.[4]

In addition, we use control variables for some global factors, namely oil prices and the global output gap. For oil prices we use average quarterly West Texas Intermediate (WTI) crude oil spot prices in US dollars transformed into quarterly log changes. The global output gap is calculated according to the same methodology as the domestic output gap, and is computed from IMF IFS data.

In some specifications, we also include inflation expectations to evaluate the pass-through according to a New-Keynesian Phillips curve setup. The end-year inflation expectations are taken from Consensus Economics. We estimate the expectation series with a quarterly frequency by subtracting realized quarterly inflation from the forecasts (Q2 and Q3), using end-year figures (Q4) or linearly interpolating end-year's estimates (Q1).

Appendix A provides a detailed description of the data including additional information on data availability.

[4]Data are available since 1995 Q1 for Hungary, Israel and Poland; since 1996 Q1 for Chile and the Czech Republic; since 1996 Q2 for India and since 1998 Q1 for the Philippines.

4.3 Method and results

4.3.1 Benchmark model

We estimate exchange rate pass-through from the following dynamic panel regression with system GMM:

$$\pi_{i,t} = \alpha_i + \beta_t + \delta\pi_{i,t-1} + \phi y_{i,t} - \sum_{j=0}^{3} \gamma_j \Delta NEER_{i,t-j} - \\ - \sum_{k=0}^{3} \mu_k \Delta NEER^2{}_{i,t-k} - \sum_{l=0}^{3} \nu_l \Delta NEER^3{}_{i,t-l} + \epsilon_{i,t} \quad (4.1)$$

Here, $\pi_{i,t}$ denotes log differences in quarterly seasonally adjusted consumer price indices (CPI) in country i in quarter t; y_{it} is the domestic output gap in country i in quarter t; ΔNEER it is the (change in the log of) the nominal effective exchange rate; α_i are country fixed effects, β_t are time (quarter) fixed effects. The estimation period is Q1 1994 – Q4 2015. To capture any non-linearities in the exchange rate pass-through, we extend the specification to include quadratic and cubic changes in exchange rates. The exchange rate terms are presented with a negative sign given that in the original series local exchange rate depreciation is reflected as a decrease in the NEER. The model works with contemporaneous exchange rate change and three additional lags to capture exchange rate pass-through over the period of one year. Furthermore, the specification also satisfies the optimal lag structure based on Akaike and Bayesian information criteria. We present estimates for advanced and emerging economies separately. We also include country fixed effects to control for unobserved country heterogeneity. Moreover, we include time fixed effects to control for global factors driving inflation.

Our estimation assumes a non-linear structure, since the underlying pass-through process may be non-linear (Bussière (2013), Ben Cheikh & Rault (2015)). Such non-linearity might arise due to menu costs, ie due to the presence of non-negligible costs of adjusting prices. Firms might prefer to avoid these menu costs when exchange rate moves are small, but could be forced to adjust prices for larger exchange rate movements (Forbes 2014). Alternatively, firms might absorb small changes in input prices but not large ones. Non-linearities might also be explained by imperfect competition which would lead to observationally similar results.[5]

[5] We have also investigated a possible role of asymmetries on exchange rate pass-through

To estimate Equation 4.1, we use generalized method of moments (GMM) following Arellano & Bover (1995) and Blundell & Bond (1998). This method has been widely used to deal with panel data with endogenous explanatory variables, and in our case it is able to control for common shocks that affect both inflation and exchange rates (Shambaugh (2008); Forbes (2015); Aron & Muellbauer (2014)). The benchmark model uses System GMM technique with 3-9 lags of log CPI changes, and 2-8 lags of NEER changes and the output gap as GMM instruments for levels and first differences equations. Later, we repeat the estimates with difference GMM and within group estimators for robustness.

Based on Equation 4.1, we estimate linear contemporaneous, yearly and long-run exchange rate pass-through. Contemporaneous linear exchange rate pass-through is defined as the coefficient on the contemporaneous log change in the NEER in Equation (4.1), ie γ_0. Yearly linear pass-through is the sum of the coefficients on log changes in the NEER over four quarters, ie $\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$. Linear long-run pass-through is defined as yearly pass-through divided by one minus the coefficient on lagged inflation, i.e. $(\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3)/(1 - \delta)$.

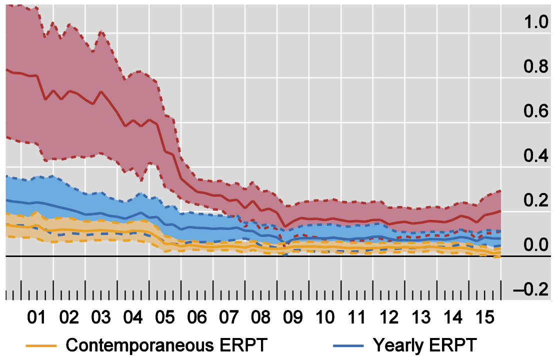
4.3.2 Evolution of pass-through

As a first step, we run the benchmark regression (4.1) on six-year windows to assess the evolution of pass-through over time Figure 4.1. We run the regression separately for emerging markets (Panel (a)) and advanced economies (Panel (b)).

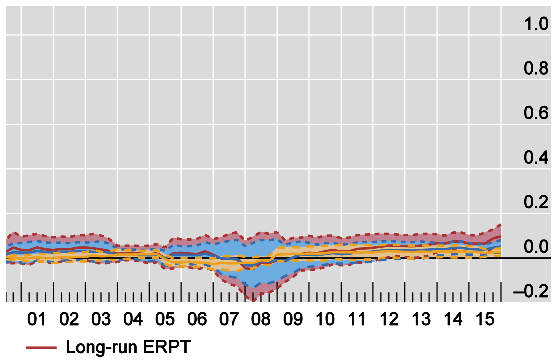
For emerging markets (Panel (a)), all three pass-through measures (contemporaneous, yearly and long-run) decline strongly from the pre-crisis levels after the financial crisis. A similar declining pattern also holds when choosing different rolling windows (see Figure 4.1). For advanced economies (Panel (b)) all three pass-through measures (contemporaneous, yearly and long-run) remain relatively stable, at low levels, throughout our estimation period. This results again holds for different rolling windows (see Appendix B Figures 4.4 and 4.5).

but in contrast to the literature on FOREX markets (Baruník *et al.* 2016), we do not find any asymetric effects on ERPT. As a consequence, we choose our main specification with a focus on non-linearities.

Figure 4.1: Exchange rate pass-through (six-year rolling windows)



(a) Emerging market economies



(b) Advanced economies
Based on Equation 4.1

In order to evaluate whether the decline in pass-through after the financial crisis was indeed significant, we add to the benchmark equation a dummy variable for the post-crisis period. The dummy variable D_t takes the value of one in the post-crisis period (Q3 2009–Q4 2015) and zero in the pre-crisis period (Q1 1994–Q2 2008) - while we omit the volatile crisis years. In sum, we estimate the following equation:

$$\begin{aligned}\pi_{i,t} = \alpha_i + \beta_t + \delta\pi_{i,t-1} + \phi y_{i,t} - \sum_{j=0}^{3}\gamma_j \Delta NEER_{i,t-j} - \\ - \sum_{k=0}^{3}\mu_k \Delta NEER^2{}_{i,t-k} - \sum_{l=0}^{3}\nu_l \Delta NEER^3{}_{i,t-l} \\ + \delta_D D_t \pi_{i,t-1} + \phi_t D_t y_{i,t} - \sum_{j=0}^{3}\gamma_{jD} D_t \Delta NEER_{i,t-j} - \\ - \sum_{k=0}^{3}\gamma_{kD} D_t \Delta NEER^2{}_{i,t-k} - \sum_{l=0}^{3}\gamma_{lD} D_t \Delta NEER^3{}_{i,t-l} + \epsilon_{i,t} \quad (4.2)\end{aligned}$$

Table 4.1 shows that the decrease in linear coefficients of the pass-through in emerging markets after the crisis is statistically significant at the one percent level for all three pass-through measures (contemporaneous, yearly and long-run), see the coefficient estimates of the post-crisis interaction dummy in column (1) of Table 4.1. By contrast, this pass-through appears to increase slightly, and mostly only at the 10% significance level, in advanced economies in the post-crisis period (Table 4.2).

For all three pass-through horizons, these results are consistent with the results reported in Figure 4.1. Table 4.1 shows that pre-crisis, an exchange rate appreciation of 10% in EMEs was associated with an average decrease in consumer prices of around 2% within the same year; post-crisis, a 10% appreciation was associated with a lower decrease in consumer prices of 0.8%. The estimates of Table 4.1 also demonstrate that the conclusion is robust to different control variables for global factors, namely to using changes in oil prices or the global output gap instead of time fixed effects, see columns (2) and (3). Table 4.1 also shows that the results are robust to including inflation expectations to evaluate the pass-through according to a New-Keynesian Phillips curve setup (see Column (4)).

For advanced economies some results seems to suggest an increase in pass-through especially when measured over the one-year or long-run horizons (see Table 4.2). While all pre-crisis pass-through estimates do not appear to be significantly different from zero, we report some positive and statistically significant post-crisis pass-through estimates. Yet, one should be careful when interpreting this: the increase in advanced economies is not robust (as, for instance, the EME post-crisis decline is). Furthermore, the magnitude of decline is also small.

Table 4.1: How did the ERPT change in EMEs since the crisis?

Dependent variable: Inflation_t	(1)	(2)	(3)	(4)
Exchange rate pass-through (pre-crisis):				
ERPT_t	0.109***	0.104***	0.105***	0.0908***
	(0.0265)	(0.0242)	(0.024)	(0.0236)
Yearly ERPT	0.200***	0.193***	0.194***	0.198***
	(0.0539)	(0.0508)	(0.0508)	(0.0504)
Long-run ERPT	0.670***	0.677***	0.678***	0.497***
	(0.135)	(0.122)	(0.123)	(0.0982)
Post-crisis interaction dummy:				
$D_t \times \text{ERPT}_t$	-0.0896***	-0.0827***	-0.0766***	-0.0746***
	(0.0261)	(0.0214)	(0.0202)	(0.0245)
$D_t \times$Yearly ERPT	-0.118***	-0.127***	-0.108**	-0.120***
	(0.041)	(0.0384)	(0.0399)	(0.0388)
$D_t \times$LR ERPT	-0.107***	-0.115***	-0.0943**	-0.110***
	(0.0378)	(0.0338)	(0.0338)	(0.0359)
Exchange rate pass-through (post-crisis):				
ERPT_t	0.0190*	0.0215*	0.0288**	0.0162
$+ D_t \times \text{ERPT}_t$	(0.011)	(0.0105)	(0.0108)	(0.0102)
Yearly ERPT	0.0820***	0.0661***	0.0853***	0.0781***
$+ D_t \times$Yearly ERPT	(0.0188)	(0.0171)	(0.0184)	(0.018)
Long-run ERPT	0.209***	0.170***	0.195***	0.160***
$+ D_t \times$ LR ERPT	(0.0521)	(0.0479)	(0.0509)	(0.0365)
Lagged dependent variable	Yes	Yes	Yes	Yes
Control variables for local l factors[a]	Yes	Yes	Yes	Yes
Control variables for global factors	Time FE	ΔOil prices	Global GDP gap	Time FE
Country FE	Yes	Yes	Yes	Yes
Countries	22	22	22	22
Observations	1,721	1,721	1,721	1,721
Sargan test[b]	0.985	1	1	0.956
Hansen test[b]	1	1	1	1
Serial correlation[c]	0.517	0.545	0.567	0.423

Pass-through coefficients, based on Equation 4.2. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full results are reported in Appendix C Table 4.7

[a] Control variables for local factors includes domestic output gap in all specifications and inflation expectations in specifications (4). [b] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.[c] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.2: How did the ERPT change in AEs since the crisis?

Dependent variable: Inflation_t	(1)	(2)	(3)	(4)
Exchange rate pass-through (pre-crisis):				
ERPT_t	0.00469	-0.000156	-0.00261	0.00618
	(0.00616)	(0.00557)	(0.00774)	(0.00605)
Yearly ERPT	0.00573	-0.00569	-0.00967	0.00795
	(0.00707)	(0.00823)	(0.013)	(0.0107)
Long-run ERPT	0.00855	-0.00806	-0.014	0.0119
	(0.0111)	(0.0111)	(0.0177)	(0.0171)
Post-crisis interaction dummy:				
$D_t \times \text{ERPT}_t$	0.0218*	0.0246**	0.00559	0.0207*
	(0.0108)	(0.011)	(0.012)	(0.0101)
$D_t \times$Yearly ERPT	0.0460**	0.0605***	0.0465*	0.0445*
	(0.0206)	(0.018)	(0.0236)	(0.0216)
$D_t \times$LR ERPT	0.0533*	0.0678***	0.0495*	0.0511*
	(0.0241)	(0.0206)	(0.0238)	(0.0253)
Exchange rate pass-through (post-crisis):				
ERPT_t	0.0265**	0.0244**	0.00299	0.0269***
$+ D_t \times \text{ERPT}_t$	(0.00889)	(0.00886)	(0.0123)	(0.00809)
Yearly ERPT	0.0518***	0.0549***	0.0368*	0.0524**
$+ D_t \times$Yearly ERPT	(0.0153)	(0.0119)	(0.0195)	(0.0169)
Long-run ERPT	0.0970***	0.0915***	0.0585*	0.0972***
$+ D_t \times$ LR ERPT	(0.0279)	(0.0175)	(0.0279)	(0.0278)
Lagged dependent variable	Yes	Yes	Yes	Yes
Control variables for local factors[a]	Yes	Yes	Yes	Yes
Control variables for global factors	Time FE	ΔOil prices	Global GDP gap	Time FE
Country FE	Yes	Yes	Yes	Yes
Countries	11	11	11	11
Observations	874	874	858	824
Sargan test[b]	0.0727	0.611	0.573	0.0607
Hansen test[b]	1	1	1	1
Serial correlation[c]	0.0255	0.0763	0.179	0.0245

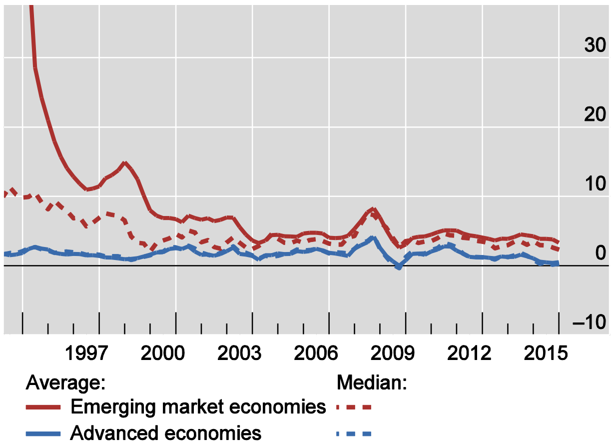
Pass-through coefficients, based on Equation 4.2. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full results are reported in Appendix C Table 4.8

[a] Control variables for local factors includes domestic output gap in all specifications and inflation expectations in specifications (4). [b] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.[c] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

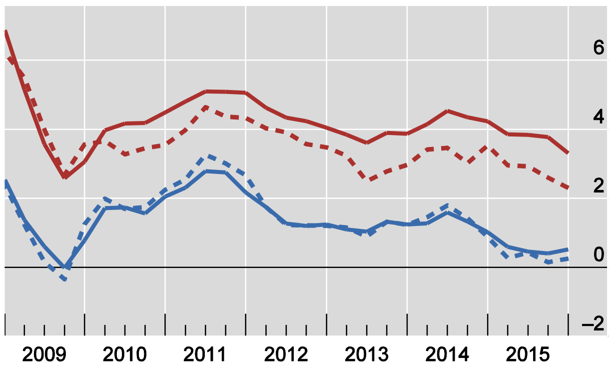
4.3.3 Pass-through and inflation

The large and significant decline in emerging market pass-through requires explanation: what has changed that could account for it? Our hypothesis is that the level of inflation affects the level of pass-through. In terms of the menu cost theory of price setting: when inflation is higher, exchange rate changes are passed through more quickly and to a larger extent because firms have to adjust prices frequently anyway.

Figure 4.2: Inflation dynamics (CPI, year-on-year changes, in %)



(a) Historical development (1994–2015)



(b) Post-crisis development (2009–2015)

Source: National data, author's calculations

Indeed, inflation has declined substantially in emerging markets in the years preceding the financial crisis, ie around the time when estimated pass-through fell too (Figure 4.2). While EME inflation was generally high in the 1990s, it fell rapidly afterwards (red line, Panel (a)). However, in spite of the fall EME inflation levels tended to remain higher than advanced economy levels even after the financial crisis (Panel (b)).

Having seen that average inflation fell around the time when inflation fell, we move to formally test whether lower inflation can indeed explain the decline in pass-through in EMEs. To do so, we add an interaction term for exchange rate movements with a four-quarter lag of inflation, to the original estimated Equation 4.1.

Formally, we estimate the below Equation 4.3:[6]

$$\begin{aligned}\pi_{i,t} = \alpha_i + \beta_t + \delta\pi_{i,t-1} + \phi y_{i,t} - \sum_{j=0}^{3}\gamma_j \Delta NEER_{i,t-j} - \\ - \sum_{k=0}^{3}\mu_k \Delta NEER^2{}_{i,t-k} - \sum_{l=0}^{3}\nu_l \Delta NEER^3{}_{i,t-l} - \\ - \sum_{j=0}^{3}\gamma_{j\pi}\pi_{it-4}\Delta NEER_{i,t-j} - \sum_{k=0}^{3}\gamma_{k\pi}\pi_{it-4}\Delta NEER^2{}_{i,t-k} - \\ - \sum_{l=0}^{3}\gamma_{l\pi}\pi_{it-4}\Delta NEER^3{}_{i,t-l} + \epsilon_{i,t} \quad (4.3)\end{aligned}$$

The results, shown in detail in Table 4.3, suggest that lower inflation can indeed explain lower pass-through at least at the yearly or long run horizons. This can be seen as the coefficient on the interaction term of linear exchange rate changes with lagged inflation is positive and significant for EMEs at these horizons.

The results provide evidence that lower inflation can induce firms to decide to adjust prices more slowly in response to exchange rate changes, consistent with the existence of menu costs. These results are robust to using changes in oil prices or the global output gap as controls for global factors instead of using time fixed effects (see Columns (2) and (3)). The results are also robust to including inflation expectations, with the interaction term for both yearly and long-run pass-through again remaining significant (see Column (4)).

[6]The four lag structure ensures that we do not interact contemporaneous inflation and exchange rate terms. However, this is not critical for our results, the results remain robust under fewer lags.

Table 4.3: Lower inflation – lower pass-through in emerging markets

Dependent variable: Inflation_t	(1)	(2)	(3)	(4)
Exchange rate pass-through:				
ERPT_t	0.0656***	0.0578***	0.0547***	0.059***
	(0.0161)	(0.0156)	(0.0169)	(0.0115)
Yearly ERPT	0.119***	0.104***	0.107***	0.121***
	(0.0268)	(0.0234)	(0.0264)	(0.0245)
Long-run ERPT	0.276***	0.254***	0.253***	0.233***
	(0.0708)	(0.0711)	(0.0754)	(0.0432)
Inflation interaction:				
$\text{Inflation}_{t\text{-}4}$	0.677	0.697	0.732	0.602
$\times\ \text{ERPT}_t$	(0.504)	(0.485)	(0.495)	(0.393)
$\text{Inflation}_{t\text{-}4}$	1.546*	1.580*	1.635*	1.460**
× Yearly ERPT	(0.787)	(0.798)	(0.803)	(0.687)
$\text{Inflation}_{t\text{-}4}$	3.578*	3.862*	3.862*	2.802**
× Long-run ERPT	(1.283)	(1.336)	(1.308)	(1.058)
Lagged dependent variable	Yes	Yes	Yes	Yes
Control variables for local factors[a]	Yes	Yes	Yes	Yes
Control variables for global factors	Time FE	ΔOil prices	Global GDP gap	Time FE
Country FE	Yes	Yes	Yes	Yes
Countries	22	22	22	22
Observations	1,809	1,809	1,779	1,809
Sargan test[b]	0.92	0.998	0.991	0.897
Hansen test[b]	1	1	1	1
Serial correlation[c]	0.636	0.621	0.737	0.537

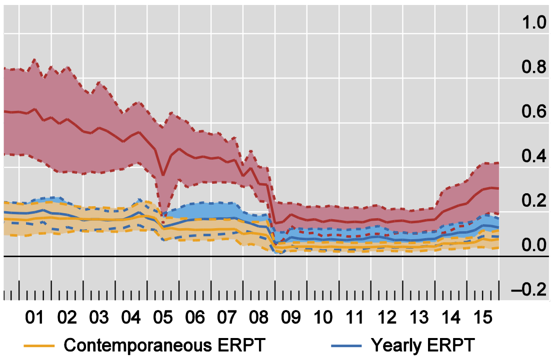
Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full results are reported in Appendix C 4.9.
[a] Control variables for local factors includes domestic output gap in all specifications and inflation expectations in specifications (4). [b] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals. [c] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

The estimated impact of lower inflation on lowering pass-through is also economically significant. The results imply that 1 percentage point lower inflation lowers the long-term average pass-through exchange rate move by around

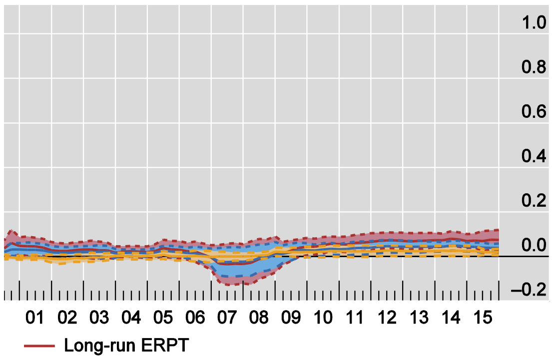
0.3–0.4 percentage points. This is a sizable impact, as the average pass-through of such a 10 percent exchange rate move is around 2.8 percentage points.

4.3.4 Omitting nonlinearity

Figure 4.3: ERPT omitting non-linear terms



(a) Emerging market economies



(b) Advanced economies

Six-year rolling windows, based on Equation 4.1

For comparison, we also present pass-through estimates when omitting the nonlinear terms in Equation 4.1. The aim of the exercise is to demonstrate that omitting these non-linear terms can cause pass-through estimates to pick up the impact of exchange rate volatility. This exercise is very relevant as nonlinear terms are often neglected in the literature.

The basic pattern in linear pass-through over time is broadly similar for both emerging markets and advanced economies (Figure 4.3). Pass-through is declining in emerging markets (Panel (a)), while it remains low and stable in advanced economies (Panel (b)). However, the linear pass-through estimates show a steady increase after mid-2013, ie following tapering of asset purchases by the

Federal Reserve and the increase of exchange rate volatility in emerging markets. These larger exchange rate movements are expected to pass-through more strongly to consumer prices than smaller movements, because they are more likely to overcome the menu costs associated with price changes. Consequently, simple linear pass-through estimates, which ignore these non-linearities, would suggest some increase in pass-through in EMEs after tapering by the Federal Reserve, while such an increase is not visible in the specification that takes non-linearities into account (Figure 4.1).

This underlines the importance of controlling for non-linearities. Furthermore, when estimating Equation 4.1, the coefficients on some of the nonlinear terms are significant for EMEs (see Appendix C Table 4.7).

4.4 Robustness

Next we extend our analysis to check the robustness of the main findings.

First, we change the size of the rolling window from six to eight, five, four and three years in the main specification of Equation 4.1 and report the results in Appendix B. We find that for all horizons (contemporaneous, yearly and long-run) the pattern for EMEs of lower linear pass-through post-crisis is robust to the length of the estimation window, for all the window sizes considered. Similarly, the pattern that the pass-through has been relatively stable in advanced economies in is preserved for different rolling window sizes.

Second, we present the results for Equation 4.3 when using log changes in bilateral exchange rates against the US dollar, instead of in NEERs (Table 4.4 and Appendix B Figure 4.6). The reason is, as Gopinath (2015) found, that the pass-through might work through the invoicing currency, typically the US dollar (USD), and not through the effective exchange rates. We find that the patterns of the pass-through estimates are roughly similar whether we use changes in the nominal exchange rate or the US dollar bilateral exchange rate, though some of our results are actually stronger when using US dollar bilateral exchange rates. For EMEs, the inflation interaction terms appear somewhat larger and more significant than in case of the NEERs. (see Table 4.5 and Appendix C Table 4.11). In particular, when using the US dollar bilateral exchange rates, the inflation interaction term also becomes significant for contemporaneous pass-through. Moreover, the coefficients on the inflation interaction terms are slightly larger for yearly and long-run pass-through, and more significant, namely at the 5% level, than when using NEERs.

Table 4.4: Lower inflation – lower pass-through: USD exchange rates

	Dependent variable: Inflation_t			
	Emerging market economies		Advanced economies	
	NEER	Bilateral USD exchange rate	NEER	Bilateral USD exchange rate
	(1)	(2)	(3)	(4)
Exchange rate pass-through:				
ERPT_t	0.0656***	0.0410**	0.00391	0.00576
	(0.0161)	(0.0173)	(0.00475)	(0.0043)
Yearly ERPT	0.119***	0.0841***	0.0167	0.0176**
	(0.0268)	(0.0172)	(0.0093)	(0.00612)
Long-run ERPT	0.276***	0.182***	0.0259	0.0280**
	(0.0708)	(0.0472)	(0.0155)	(0.0113)
Inflation interaction:				
$\text{Inflation}_{t\text{-}4} \times \text{ERPT}_t$	0.677	0.955*	1.557	0.825
	(0.504)	(0.549)	(1.226)	(0.608)
$\text{Inflation}_{t\text{-}4} \times$Yearly ERPT	1.546*	1.831**	0.936	0.784
	(0.787)	(0.759)	(1.314)	(1.131)
$\text{Inflation}_{t\text{-}4} \times$Long-run ERPT	3.578*	3.969**	1.454	1.248
	(1.283)	(1.113)	(1.895)	(1.639)
Lagged dependent variable	Yes	Yes	Yes	Yes
Control variables for local factors	Domestic GDP gap	Domestic GDP gap	Domestic GDP gap	Domestic GDP gap
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Countries	22	22	11	10
Observations	1,809	1,809	918	834
Sargan test[a]	0.92	0.775	0.229	0.19
Hansen test[a]	1	1	1	1
Serial correlation test[b]	0.636	0.66	0.0566	0.067

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full results are reported in Appendix C Table 4.11.
[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals. [b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Third, our results also remain robust to changes in the empirical estimation techniques. While our benchmark specification was system GMM, the results remain materially unchanged when using difference GMM and within group estimators (Table 4.5). This suggests that the methodological choice is not critical for our results. In all three cases we also test for different lag structures of instrumental variables to confirm that the results do not depend on the instru-

Table 4.5: Lower inflation – lower pass-through: Different methodologies

	Dependent variable: $Inflation_t$					
	Emerging market economies			Advanced economies		
	System GMM (1)	Difference GMM (2)	Within group estimator (3)	System GMM (4)	Difference GMM (5)	Within group estimator (6)
Exchange rate pass-through:						
$ERPT_t$	0.0656***	0.0565***	0.0567***	0.00391	0.00176	0.00176
	(0.0161)	(0.0144)	(0.0141)	(0.00475)	(0.00446)	(0.00445)
Yearly ERPT	0.119***	0.109***	0.108***	0.0167	0.0296***	0.0296***
	(0.0268)	(0.0234)	(0.023)	(0.0093)	(0.00806)	(0.00804)
Long-run ERPT	0.276***	0.210***	0.211***	0.0259	0.0350***	0.0350***
	(0.0708)	(0.049)	(0.0481)	(0.0155)	(0.0106)	(0.0105)
Inflation interaction:						
$Inflation_{t-4}$	0.677	0.700	0.687	1.557	2.503**	2.503**
$\times$ $ERPT_t$	(0.504)	(0.497)	(0.489)	(1.226)	(1.1)	(1.096)
$Inflation_{t-4}$	1.546*	1.692**	1.670**	0.936	2.065	2.065
$\times$ Yearly ERPT	(0.787)	(0.755)	(0.739)	(1.314)	(1.34)	(1.336)
$Inflation_{t-4}$	3.578*	3.265**	3.247**	1.454	2.438	2.438
$\times$ Long-run ERPT	(1.283)	(1.062)	(1.049)	(1.895)	(1.485)	(1.48)
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes
Control variables for local factors	Domestic GDP gap	Domestic GDP gap	Domestic GDP gap	Domestic GDPgap	Domestic GDP gap	Domestic GDP gap
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	22	22	22	11	11	11
Observations	1,809	1,787	1,809	918	907	918
Sargan test[a]	0.92	0.604		0.229	0.0111	
Hansen test[a]	1	1		1	1	
Serial correlation[b]	0.636	0.705		0.0566	0.251	
Within R^2			0.814			0.467

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full results are reported in Appendix C Table 4.12.
[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals. [b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

ment lag choice (Appendix C Table 4.13). Furthermore, the basic pattern: the post-crisis decrease for EMEs and relative stability of pass-through for advanced economies, remains unchanged for all three pass-through horizons.

Furthermore, we also modify the main specification to allow for asymmetry in pass-through for exchange rate depreciations and appreciations. However, we do not find evidence for consistent asymmetries when estimating the exchange rate pass-through separately for depreciations and appreciations.

4.4.1 Caveats

However, the results should be read with appropriate caveats. Importantly, they apply only for groups of countries, and not for individual economies. In particular, while we see a large drop in pass-through for emerging markets as a group after the financial crisis, some emerging economies could still have experienced stable or even increasing pass-through. Similarly, in spite of the stable average results, different pass-through trends might prevail in some advanced economies.

Furthermore, our setup is limited to macroeconomic factors, while microeconomic factors, such as price competition or pricing-to-market, might also play a role in determining pass-through (Campa & Goldberg 2005). For instance, the more oligopolistic/less price taking behaviour is the weaker pass-through from input prices (which might be affected by exchange rate movements) to final prices is. However, these concerns are mitigated by the fact that our setup captures the time-invariant microeconomic factors by the country fixed effects. Further mitigation, as Forbes (2015) argues, is that these structural microeconomic differences might matter less than thought earlier: recent pass-through estimates for the United Kingdom do not show much difference between goods with differing import content, or between economic sectors with different tradability or degree of international competition.

Another caveat arises due to new limitations in monetary policy, namely reaching the zero lower bound and in some cases outright negative interest rates. To the degree that this constrains monetary policy, pass-though could be affected. Having said that, this constraint is unlikely to affect our main conclusion: First, there is no such constraint in emerging markets where we see a larger decline in pass-through. Second, pass-through estimates seem to remain low in advanced economies even under low interest rates. Yet, this issue highlights that one should not be complacent about low pass-through in advanced economies: the slight and not very robust increase in pass-through in some of our estimates shown for advanced economies could warrant further investigation and research in light of these policy constraints.

Finally, our approach does not distinguish between exogenous and endogenous exchange rate shocks - and this distinction might matter as Forbes (2015) and Shambaugh (2008) show. However, we consciously control for global factors, either through time fixed effects or explicitly, in order to consistently exclude global shocks.[7] On the one hand, this exclusion of global factors is reassuring: the results are not contaminated by shifting global shocks. On the other hand, this also implies that the inclusion of global shocks could add further dynamics in principle - though our tests suggests that removing the time-fixed effects does not materially affect the main results.[8]

4.5 Conclusions

We studied how exchange rate pass-through has changed since the global financial crisis. We found that exchange rate pass-through to CPI inflation in emerging economies decreased in the wake of the financial crisis, and that this decline in pass-through in emerging economies is linked to declining inflation. By contrast, exchange rate pass-through in advanced economies has remained relatively stable over time, at a lower level than in emerging economies. These results hold for both short-run and long-run pass-through. The results are found to be robust to a range of controls and specifications.

The results have policy relevance, particularly when assessing broad changes in how exchange rate changes are transmitted to consumer prices in the global economy. Providing such a global context might help thinking about monetary policy in many countries, even if the pass-through estimates are not directly applicable to any individual country. In this regard, the generally low pass-through levels today imply that central banks in general should "fear" less the "floating" of their exchange rates, at least from an inflation perspective. Yet, the lower pass-through in emerging markets also implies that the exchange rate channel of monetary policy might be less effective to affect inflation than before the financial crisis. Finally, the results further confirm the importance of price stability by showing that lower inflation, among its other benefits, also reduces exchange rate pass-through to consumer prices.

[7] The dynamic panel estimates in the baseline specification include time fixed effects and thereby the pass-through estimates are derived only from the cross-sectional variation.

[8] We explored this point above by running our specification without time fixed effects for robustness (see Columns (2) and (3) of Tables 4.1, 4.2 and 4.3 and for robustness).

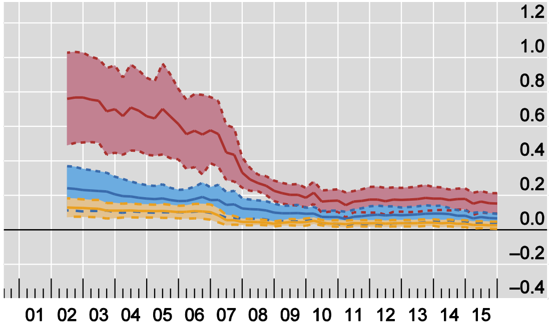
Appendix A: Data sources

Table 4.6: ERPT: Data sources

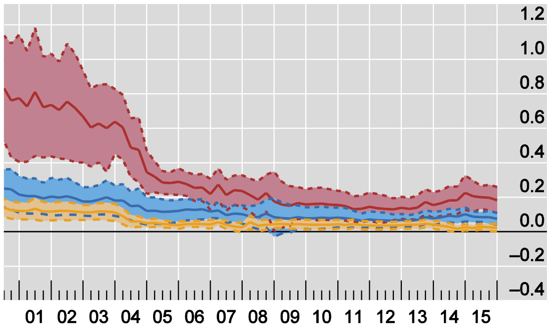
Variable	Description	Source
Inflation		
Consumer price index	Quarter-on-quarter log changes, seasonally adjusted.	Datastream National data BIS
Exchange rates		
Nominal effective exchange rates	Nominal effective exchange rate indices are calculated as geometric weighted averages of bilateral exchange rates. Broad indices comprise of 61 economies, with data from 1994. Quarterly averages, quarter-on-quarter log changes.	BIS
Bilateral USD exchange rates	Bilateral US dollar exchange rate against local currency. Quarterly averages, quarter-on-quarter log changes.	National data BIS S
Control variables for local factors		
Domestic output gap	Standard Hodrick-Prescott filter applied on quarterly real GDP series. GDP in levels; domestic currency units.	National data BIS Authors' calculations
Inflation expectations	Quarter-on-quarter inflation Data are derived from yearly Consensus surveys' inflation expectations by assuming constant inflation over the coming quarters within the year.	Consensus Economics Datastream National data BIS Authors' calculations
Control variables for global factors		
Oil prices	West Texas Intermediate (WTI) crude oil spot price. Quarterly averages, quarter-on-quarter log changes.	Bloomberg
Global output gap	Standard Hodrick-Prescott filter applied on quarterly real GDP series.	IMF IFS Authors' calculations

Appendix B: Robustness test: Rolling windows

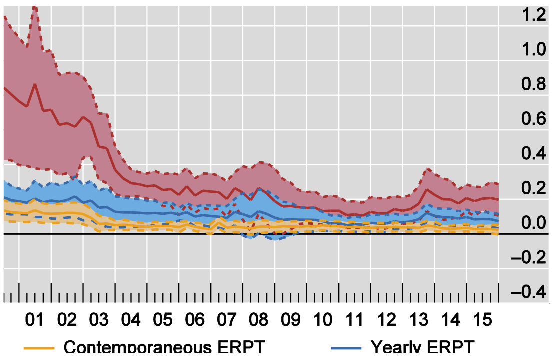
Figure 4.4: Robustness: ERPT to emerging markets



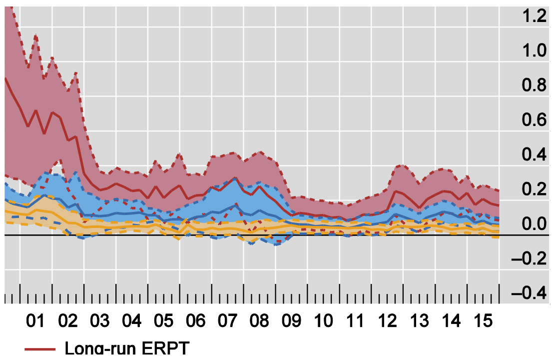
(a) Eight-year window



(b) Five-year window



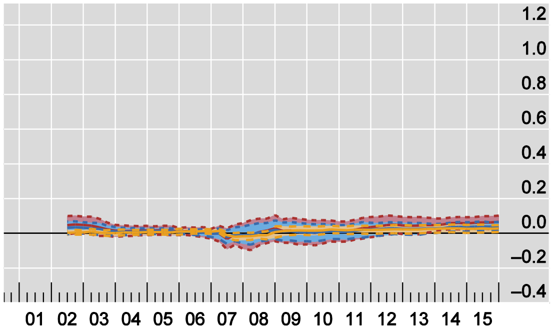
(c) Four-year window



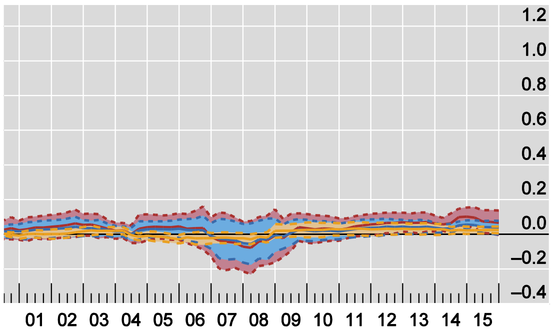
(d) Three-year window

Baseline specification with different rolling window sizes

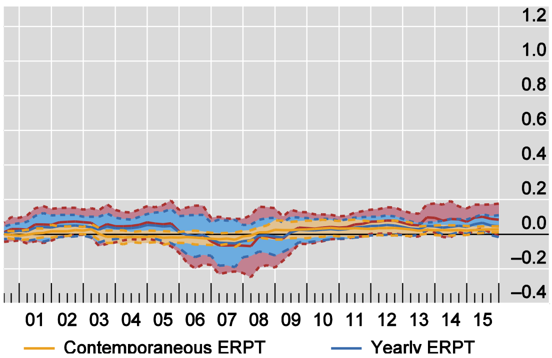
Figure 4.5: Robustness: ERPT to advanced economies



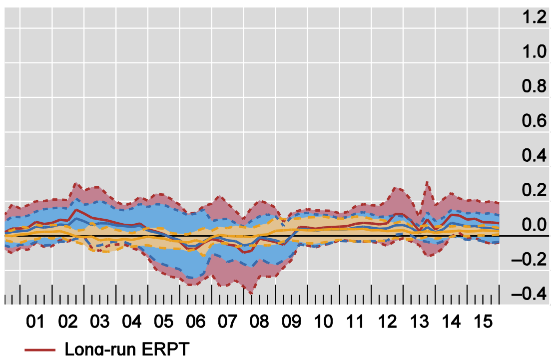
(a) Eight-year window



(b) Five-year window



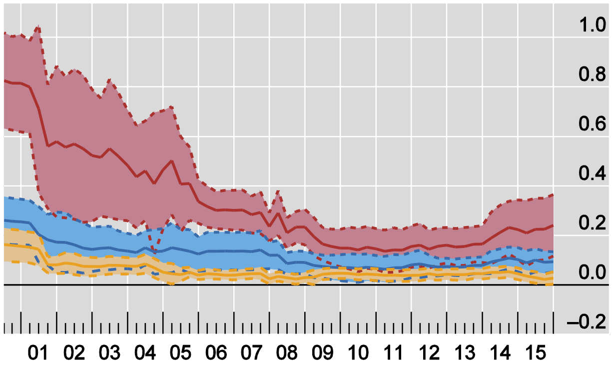
(c) Four-year window



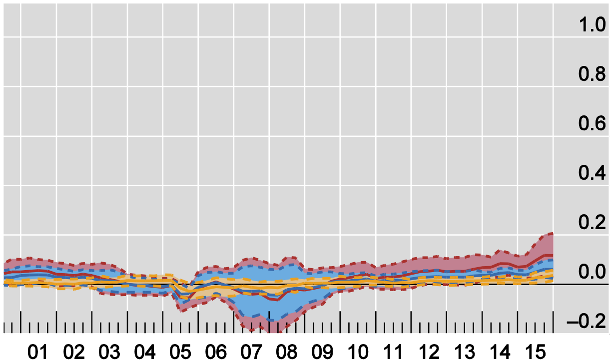
(d) Three-year window

Baseline specification with different rolling window sizes

Figure 4.6: Robustness: ERPT using bilateral USD exchange rate



(a) Emerging markets



(b) Advanced economies

Six-year rolling windows, based on equation 4.1

Appendix C: Full results

Table 4.7: Robustness: ERPT to emerging markets

Dependent variable: Inflation_t				
	Emerging market economies			
	(1)	(2)	(3)	(4)
Inflation_{t-1}	0.702***	0.715***	0.714***	0.601***
	(0.028)	(0.0274)	(0.0269)	(0.037)
ΔNEER_t	0.109***	0.104***	0.105***	0.0908***
$=ERPT_t$	(0.0265)	(0.0242)	(0.024)	(0.0236)
ΔNEER_{t-1}	0.0584**	0.0580**	0.0580**	0.0626**
	(0.0236)	(0.025)	(0.0251)	(0.0235)
ΔNEER_{t-2}	0.00472	0.00283	0.0031	0.0088
	(0.0194)	(0.015)	(0.015)	(0.0211)
ΔNEER_{t-3}	0.0278***	0.0278***	0.0273***	0.0361***
	(0.00765)	(0.00758)	(0.0074)	(0.0108)
$\Delta\text{NEER}_t{}^2$	0.144	0.143	0.151	0.159**
	(0.104)	(0.116)	(0.114)	(0.076)
$\Delta\text{NEER}_{t-1}{}^2$	-0.0943	-0.0799	-0.0805	-0.0811
	(0.121)	(0.131)	(0.131)	(0.109)
$\Delta\text{NEER}_{t-2}{}^2$	0.112	0.123	0.119	0.156**
	(0.0732)	(0.0746)	(0.075)	(0.0707)
$\Delta\text{NEER}_{t-3}{}^2$	-0.012	-0.0118	-0.0139	0.0427
	(0.0453)	(0.0425)	(0.0419)	(0.051)
$\Delta\text{NEER}_t{}^3$	0.295***	0.305***	0.311***	0.320***
	(0.102)	(0.103)	(0.1)	(0.0981)
$\Delta\text{NEER}_{t-1}{}^3$	-0.198	-0.181	-0.184	-0.174
	(0.169)	(0.183)	(0.182)	(0.156)
$\Delta\text{NEER}_{t-2}{}^3$	0.0652	0.0854	0.0805	0.138
	(0.123)	(0.129)	(0.126)	(0.124)
$\Delta\text{NEER}_{t-3}{}^3$	-0.0392	-0.0385	-0.0389	0.00909
	(0.0515)	(0.0505)	(0.0497)	(0.0454)
Output gap_t	-0.0104	0.0268	0.00513	0.0199
	(0.0363)	(0.0336)	(0.0371)	(0.0241)
$D_t \times \text{Inflation}_{t-1}$	-0.094	-0.105**	-0.151***	-0.0902**
	(0.0661)	(0.0453)	(0.0469)	(0.0373)
$D_t \times \Delta\text{NEER}_t$	-0.0896***	-0.0827***	-0.0766***	-0.0746***

$= D_t \times ERPT_t$	(0.0261)	(0.0214)	(0.0202)	(0.0245)
$D_t \times \Delta NEER_{t-1}$	-0.0116	-0.0206	-0.0165	-0.017
	(0.0203)	(0.0213)	(0.0213)	(0.0203)
$D_t \times \Delta NEER_{t-2}$	0.00139	0.00324	0.00515	0.00215
	(0.0214)	(0.0173)	(0.0175)	(0.022)
$D_t \times \Delta NEER_{t-3}$	-0.0177	-0.0268**	-0.0205*	-0.0308*
	(0.0109)	(0.00981)	(0.0102)	(0.0151)
$D_t \times \Delta NEER_t{}^2$	-0.143	-0.159	-0.232	-0.244
	(0.268)	(0.256)	(0.271)	(0.255)
$D_t \times \Delta NEER_{t-1}{}^2$	-0.052	0.0103	-0.246	-0.0877
	(0.178)	(0.176)	(0.232)	(0.147)
$D_t \times \Delta NEER_{t-2}{}^2$	-0.0204	-0.0895	-0.194	-0.0454
	(0.142)	(0.121)	(0.135)	(0.131)
$D_t \times \Delta NEER_{t-3}{}^2$	-0.157	-0.278***	-0.330***	-0.139
	(0.117)	(0.097)	(0.107)	(0.111)
$D_t \times \Delta NEER_t{}^3$	2.811***	2.652***	2.282***	2.398***
	(0.364)	(0.362)	(0.258)	(0.292)
$D_t \times \Delta NEER_{t-1}{}^3$	-0.656	-0.231	-1.727**	-0.775
	(0.447)	(0.43)	(0.74)	(0.489)
$D_t \times \Delta NEER_{t-2}{}^3$	-0.72	-0.874*	-0.957*	-0.855*
	(0.53)	(0.478)	(0.512)	(0.496)
$D_t \times \Delta NEER_{t-3}{}^3$	-0.713	-1.059**	-1.209**	-0.433
	(0.482)	(0.491)	(0.579)	(0.477)
$D_t \times$Output gap_t	0.0303	-0.0158	-0.026	0.000481
	(0.0427)	(0.0374)	(0.04)	(0.0342)
ΔOil $prices_t$		0.00718***		
		(0.00201)		
Global output gap_t			0.123***	
			(0.0395)	
Inflation $expectations_{t+1}$				0.165***
				(0.0197)
Constant	0.000698	0.00329***	0.00340***	0.000114
	(0.00191)	(0.000641)	(0.000578)	(0.00171)
Yearly ERPT	0.200***	0.193***	0.194***	0.198***
	(0.0539)	(0.0508)	(0.0508)	(0.0504)
Long-run ERPT	0.670***	0.677***	0.678***	0.497***
	(0.135)	(0.122)	(0.123)	(0.0982)
$D_t \times YearlyERPT$	-0.118***	-0.127***	-0.108**	-0.120***

	(0.041)	(0.0384)	(0.0399)	(0.0388)
D_t $\times$*LR ERPT*	-0.107***	-0.115***	-0.0943**	-0.110***
	(0.0378)	(0.0338)	(0.0338)	(0.0359)
$ERPT_t$	0.0190*	0.0215*	0.0288**	0.0162
+ $D_t\times$ $ERPT_t$	(0.011)	(0.0105)	(0.0108)	(0.0102)
Yearly ERPT	0.0820***	0.0661***	0.0853***	0.0781***
+ $D_t\times$*Yearly ERPT*	(0.0188)	(0.0171)	(0.0184)	(0.018)
Long-run ERPT	0.209***	0.170***	0.195***	0.160***
+ $D_t\times$*LR ERPT*	(0.0521)	(0.0479)	(0.0509)	(0.0365)
Observations	1721	1721	1691	1721
Countries	22	22	22	22
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes
Sargan test[a]	0.985	1	1	0.956
Hansen test[a]	1	1	1	1
Serial correlation[b]	0.517	0.545	0.567	0.423

Pass-through coefficients, based on Equation 4.2. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.8: Robustness: ERPT to advanced economies

Dependent variable: Inflation_t				
	Advanced economies			
	(1)	(2)	(3)	(4)
Inflation_{t-1}	0.330***	0.294***	0.311***	0.330***
	(0.0989)	(0.0828)	(0.0894)	(0.0875)
ΔNEER_t	0.00469	-0.00016	-0.00261	0.00618
$=ERPT_t$	(0.00616)	(0.00557)	(0.00774)	(0.00605)
ΔNEER_{t-1}	0.00347	0.0027	0.00193	0.00244
	(0.00989)	(0.00898)	(0.00768)	(0.0106)
ΔNEER_{t-2}	0.00131	0.00127	0.00238	0.00185
	(0.00763)	(0.00685)	(0.00651)	(0.0101)
ΔNEER_{t-3}	-0.00373	-0.00951	-0.0114	-0.00252
	(0.0106)	(0.00736)	(0.00754)	(0.011)
$\Delta\text{NEER}_t{}^2$	0.0517	-0.100	-0.0892	0.0538
	(0.17)	(0.138)	(0.189)	(0.181)
$\Delta\text{NEER}_{t-1}{}^2$	-0.0639	-0.0304	0.0145	-0.0795
	(0.403)	(0.294)	(0.27)	(0.394)
$\Delta\text{NEER}_{t-2}{}^2$	0.258	0.192	0.173	0.249
	(0.221)	(0.157)	(0.204)	(0.25)
$\Delta\text{NEER}_{t-3}{}^2$	0.0622	0.0924	0.0307	0.0978
	(0.223)	(0.209)	(0.226)	(0.233)
$\Delta\text{NEER}_t{}^3$	-1.576	0.271	0.313	-1.721
	(0.987)	(1.425)	(1.846)	(0.995)
$\Delta\text{NEER}_{t-1}{}^3$	2.681	3.37	2.955	2.837
	(2.548)	(2.024)	(2.027)	(2.753)
$\Delta\text{NEER}_{t-2}{}^3$	0.0024	0.956	-0.398	0.258
	(1.03)	(1.313)	(1.541)	(1.083)
$\Delta\text{NEER}_{t-3}{}^3$	0.996	2.05	1.534	0.848
	(1.487)	(1.18)	(1.289)	(1.676)
Output gap_t	0.0283*	0.0509***	0.0590***	0.0261
	(0.0147)	(0.00795)	(0.0157)	(0.0149)
$D_t \times \text{Inflation}_{t-1}$	0.137	0.106	0.0601	0.13
	(0.115)	(0.0722)	(0.082)	(0.127)
$D_t \times \Delta\text{NEER}_t$	0.0218*	0.0246**	0.00559	0.0207*
$= D_t \times ERPT_t$	(0.0108)	(0.011)	(0.012)	(0.0101)

$D_t \times \Delta NEER_{t-1}$	0.0168	0.0165	0.0148	0.0182
	(0.0137)	(0.0121)	(0.00929)	(0.0148)
$D_t \times \Delta NEER_{t-2}$	-0.00633	-0.00334	-0.00601	-0.00698
	(0.0118)	(0.0123)	(0.0127)	(0.0132)
$D_t \times \Delta NEER_{t-3}$	0.0138	0.0228**	0.0321**	0.0125
	(0.0127)	(0.00995)	(0.0115)	(0.0127)
$D_t \times \Delta NEER_t^2$	0.168	0.331**	0.799***	0.163
	(0.188)	(0.135)	(0.151)	(0.186)
$D_t \times \Delta NEER_{t-1}^2$	-0.178	-0.157	-0.337	-0.167
	(0.367)	(0.369)	(0.308)	(0.375)
$D_t \times \Delta NEER_{t-2}^2$	-0.309	-0.16	-0.258	-0.303
	(0.278)	(0.183)	(0.244)	(0.295)
$D_t \times \Delta NEER_{t-3}^2$	0.0379	-0.0147	0.0454	0.00464
	(0.217)	(0.214)	(0.226)	(0.212)
$D_t \times \Delta NEER_t^3$	0.813	-1.573	3.38	0.902
	(1.884)	(2.513)	(2.812)	(1.847)
$D_t \times \Delta NEER_{t-1}^3$	-5.221	-6.421**	-6.418*	-5.422
	(3.559)	(2.715)	(3.034)	(3.549)
$D_t \times \Delta NEER_{t-2}^3$	-0.103	-0.96	0.0153	-0.304
	(1.856)	(1.812)	(2.357)	(1.842)
$D_t \times \Delta NEER_{t-3}^3$	-0.814	-2.008*	-1.556	-0.668
	(1.412)	(1.094)	(1.31)	(1.586)
$D_t \times$ Output gap_t	-0.0191	-0.0489	-0.100**	-0.0158
	(0.0453)	(0.0332)	(0.0413)	(0.0449)
ΔOil $prices_t$		0.0123***		
		(0.00125)		
Global output			0.0207	
gap_t			(0.0243)	
Inflation				0.0157
$expectations_{t+1}$				(0.107)
Constant	0.000913	0.00272***	0.00292***	0.000449
	(0.000687)	(0.000512)	(0.000523)	(0.00184)
Yearly ERPT	0.00573	-0.00569	-0.00967	0.00795
	(0.00707)	(0.00823)	(0.013)	(0.0107)
Long-run ERPT	0.00855	-0.00806	-0.014	0.0119
	(0.0111)	(0.0111)	(0.0177)	(0.0171)
$D_t \times$ *Yearly ERPT*	0.0460**	0.0605***	0.0465*	0.0445*
	(0.0206)	(0.018)	(0.0236)	(0.0216)

$D_t \times LR\ ERPT$	0.0533*	0.0678***	0.0495*	0.0511*
	(0.0241)	(0.0206)	(0.0238)	(0.0253)
$ERPT_t$	0.0265**	0.0244**	0.00299	0.0269***
$+ D_t \times\ ERPT_t$	(0.00889)	(0.00886)	(0.0123)	(0.00809)
Yearly ERPT	0.0518***	0.0549***	0.0368*	0.0524**
$+ D_t \times$ *Yearly ERPT*	(0.0153)	(0.0119)	(0.0195)	(0.0169)
Long-run ERPT	0.0970***	0.0915***	0.0585*	0.0972***
$+ D_t \times LR\ ERPT$	(0.0279)	(0.0175)	(0.0279)	(0.0278)
Observations	874	874	858	824
Countries	11	11	11	11
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes
Sargan test[a]	0.0727	0.611	0.573	0.0607
Hansen test[a]	1	1	1	1
Serial correlation[b]	0.0255	0.0763	0.179	0.0245

Pass-through coefficients, based on Equation 4.2. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.9: Lower inflation - lower pass-through: EMEs

Dependent variable: Inflation_t				
	Emerging market economies			
	(1)	(2)	(3)	(4)
$\text{Inflation}_{t\text{-}1}$	0.568***	0.591***	0.577***	0.479***
	(0.0724)	(0.0713)	(0.0713)	(0.0619)
ΔNEER_t	0.0656***	0.0578***	0.0547***	0.0590***
$= ERPT_t$	(0.0161)	(0.0156)	(0.0169)	(0.0115)
$\Delta\text{NEER}_{t\text{-}1}$	0.0268**	0.0243**	0.0249**	0.0254**
	(0.0124)	(0.0112)	(0.0116)	(0.0111)
$\Delta\text{NEER}_{t\text{-}2}$	-0.00472	-0.00632	-0.0031	0.00236
	(0.0148)	(0.012)	(0.0123)	(0.0158)
$\Delta\text{NEER}_{t\text{-}3}$	0.0316**	0.0283**	0.0304***	0.0346***
	(0.0122)	(0.011)	(0.0106)	(0.0109)
$\Delta\text{NEER}_t{}^2$	0.0243	0.0199	0.0322	0.0731
	(0.0633)	(0.0638)	(0.0619)	(0.0683)
$\Delta\text{NEER}_{t\text{-}1}{}^2$	-0.0972	-0.075	-0.0823	-0.107
	(0.126)	(0.129)	(0.127)	(0.11)
$\Delta\text{NEER}_{t\text{-}2}{}^2$	0.0858	0.0961	0.0759	0.124
	(0.105)	(0.101)	(0.104)	(0.0941)
$\Delta\text{NEER}_{t\text{-}3}{}^2$	-0.0788	-0.0831	-0.0923	-0.00274
	(0.0597)	(0.0606)	(0.0601)	(0.0628)
$\Delta\text{NEER}_t{}^3$	0.230**	0.245***	0.262***	0.278**
	(0.0958)	(0.083)	(0.0889)	(0.118)
$\Delta\text{NEER}_{t\text{-}1}{}^3$	-0.117	-0.0905	-0.101	-0.122
	(0.137)	(0.138)	(0.138)	(0.121)
$\Delta\text{NEER}_{t\text{-}2}$	0.0724	0.0912	0.062	0.137
	(0.102)	(0.104)	(0.103)	(0.0996)
$\Delta\text{NEER}_{t\text{-}3}$	-0.150**	-0.152**	-0.164**	-0.0481
	(0.0714)	(0.0683)	(0.0696)	(0.0732)
Output gap_t	-0.0121	0.0285	0.00566	0.0131
	(0.0277)	(0.0282)	(0.034)	(0.018)
$\text{Inflation}_{t\text{-}4} \times \Delta\text{NEER}_t$	0.677	0.697	0.732	0.602
$= Inflation_{t\text{-}4} \times ERPT_t$	(0.504)	(0.485)	(0.495)	(0.393)
$\text{Inflation}_{t\text{-}4} \times \Delta\text{NEER}_{t\text{-}1}$	0.610**	0.620**	0.633**	0.677**
	(0.234)	(0.253)	(0.249)	(0.252)
$\text{Inflation}_{t\text{-}4} \times \Delta\text{NEER}_{t\text{-}2}$	0.309*	0.312*	0.322*	0.237
	(0.175)	(0.171)	(0.175)	(0.154)
$\text{Inflation}_{t\text{-}4} \times \Delta\text{NEER}_{t\text{-}3}$	-0.0502	-0.0492	-0.0522	-0.0557
	(0.0736)	(0.0735)	(0.0753)	(0.0551)

ΔOil prices$_t$		0.0122***		
		(0.00181)		
Global output gap$_t$			0.123***	
			(0.0423)	
Inflation expectations$_{t+1}$				0.162***
				(0.0266)
Constant	0.00691	0.0041***	0.0045***	0.00565
	(0.00583)	(0.00074)	(0.00075)	(0.00685)
Yearly ERPT	0.118***	0.103***	0.107***	0.120***
	(0.0266)	(0.0234)	(0.0264)	(0.0243)
Long-run ERPT	0.274***	0.252***	0.252***	0.231***
	(0.0702)	(0.0709)	(0.0751)	(0.0429)
Inflation$_{t\text{-}4}\times$*Yearly ERPT*	1.550*	1.584*	1.637*	1.464**
	(0.786)	(0.797)	(0.802)	(0.686)
Inflation$_{t\text{-}4}\times$*Long-run ERPT*	3.589*	3.873*	3.867*	2.812
	(1.281)	(1.336)	(1.307)	(1.059)
Observations	1832	1832	1801	1832
Countries	23	23	23	23
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes
Sargan test[a]	0.926	0.999	0.992	0.905
Hansen test[a]	1.000	1.000	1.000	1.000
Serial correlation test[b]	0.635	0.618	0.736	0.536

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.10: Lower inflation - lower pass-through: AEs

Dependent variable: Inflation_{t}				
	Advanced economies			
	(1)	(2)	(3)	(4)
$\text{Inflation}_{t\text{-}1}$	0.356***	0.331***	0.310***	0.347***
	(0.0844)	(0.0734)	(0.0767)	(0.0691)
ΔNEER_{t}	0.00391	0.00487	-0.00054	0.00494
$=ERPT_t$	(0.00475)	(0.00354)	(0.00737)	(0.00498)
$\Delta\text{NEER}_{t\text{-}1}$	0.0111	0.00868	0.00422	0.0111
	(0.00738)	(0.00646)	(0.00709)	(0.00722)
$\Delta\text{NEER}_{t\text{-}2}$	0.00312	0.00288	0.00025	0.00484
	(0.0048)	(0.00275)	(0.00468)	(0.00621)
$\Delta\text{NEER}_{t\text{-}3}$	-0.00142	-0.00139	-0.00171	-0.00023
	(0.00382)	(0.00345)	(0.00493)	(0.0037)
$\Delta\text{NEER}_{t}{}^{2}$	0.0516	0.077	0.297**	0.05
	(0.0538)	(0.0595)	(0.133)	(0.0599)
$\Delta\text{NEER}_{t\text{-}1}{}^{2}$	0.00849	0.0297	0.0978	0.00483
	(0.112)	(0.0692)	(0.0652)	(0.103)
$\Delta\text{NEER}_{t\text{-}2}{}^{2}$	0.0457**	0.0783**	-0.0824	0.0406**
	(0.016)	(0.0345)	(0.058)	(0.0149)
$\Delta\text{NEER}_{t\text{-}3}{}^{2}$	0.061	0.014	-0.0338	0.0696
	(0.047)	(0.0407)	(0.049)	(0.0518)
$\Delta\text{NEER}_{t}{}^{3}$	0.0168	0.0782	0.588	-0.0613
	(0.278)	(0.235)	(0.401)	(0.357)
$\Delta\text{NEER}_{t\text{-}1}{}^{3}$	0.0844	0.0961	0.232	0.0474
	(0.289)	(0.255)	(0.329)	(0.223)
$\Delta\text{NEER}_{t\text{-}2}{}^{3}$	0.468	0.359	0.214	0.475
	(0.286)	(0.234)	(0.273)	(0.325)
$\Delta\text{NEER}_{t\text{-}3}{}^{3}$	0.540*	0.655**	0.553**	0.531*
	(0.269)	(0.246)	(0.24)	(0.287)
Output gap_{t}	0.0330*	0.0451***	0.0414**	0.0326**
	(0.0148)	(0.0123)	(0.0172)	(0.0144)
$\text{Inflation}_{t\text{-}4}\times\Delta\text{NEER}_{t}$	1.557	1.139	0.0175	1.65
$=\mathit{Inflation}_{t\text{-}4}\times ERPT_t$	(1.226)	(0.812)	(1.382)	(1.202)
$\text{Inflation}_{t\text{-}4}\times\Delta\text{NEER}_{t\text{-}1}$	-0.11	0.159	-0.0533	-0.0175
	(0.564)	(0.751)	(0.801)	(0.523)
$\text{Inflation}_{t\text{-}4}\times\Delta\text{NEER}_{t\text{-}2}$	-1.029*	-0.555	-0.0121	-1.243**
	(0.554)	(0.485)	(0.744)	(0.5)
$\text{Inflation}_{t\text{-}4}\times\Delta\text{NEER}_{t\text{-}3}$	0.519	0.0329	0.301	0.457
	(0.588)	(0.463)	(0.436)	(0.821)

ΔOil prices$_t$		0.0126***		
		(0.00142)		
Global output gap$_t$			0.028	
			(0.0223)	
Inflation expectationst$_{t+1}$				0.0446
				(0.111)
Constant	0.00119	0.0028***	0.0031***	0.00105
	(0.001)	(0.00058)	(0.0006)	(0.00115)
Yearly ERPT	0.0167	0.0150*	0.00222	0.0206*
	(0.0093)	(0.0077)	(0.0124)	(0.011)
Long-run ERPT	0.0259	0.0225	0.00322	0.0316
	(0.0155)	(0.0129)	(0.0182)	(0.0186)
Inflation$_{t-4}$ $\times$*Yearly ERPT*	0.936	0.776	0.253	0.846
	(1.314)	(1.071)	(1.221)	(1.431)
Inflation$_{t-4}$ $\times$*Long-run ERPT*	1.454	1.16	0.367	1.297
	(1.895)	(1.489)	(1.741)	(2.085)
Observations	918	918	902	868
Countries	11	11	11	11
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes
Sargan test[a]	0.229	0.891	0.617	0.221
Hansen test[a]	1.000	1.000	1.000	1.000
Serial correlation test[b]	0.0566	0.0753	0.627	0.0561

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.11: Robustness: USD vs NEER

Dependent variable: $Inflation_t$				
	Emerging economies			
	(1)	(2)	(3)	(4)
Explanatory variables	NEER	Bilateral USD exchange rate	NEER	Bilateral exchange rate
$Inflation_{t-1}$	0.568***	0.539***	0.356***	0.372***
	(0.0724)	(0.0695)	(0.0844)	(0.0939)
ΔExchange $rate_t$	0.0656***	0.0410**	0.00391	0.00576
$=ERPT_t$	(0.0161)	(0.0173)	(0.00475)	(0.0043)
ΔExchange $rate_{t-1}$	0.0268**	0.0315**	0.0111	0.0103
	(0.0124)	(0.0138)	(0.00738)	(0.00586)
ΔExchange $rate_{t-2}$	-0.00472	-0.0248	0.00312	0.00027
	(0.0148)	(0.0183)	(0.0048)	(0.00547)
ΔExchange $rate_{t-3}$	0.0316**	0.0364**	-0.00142	0.00125
	(0.0122)	(0.0129)	(0.00382)	(0.00423)
ΔExchange $rate_t{}^2$	0.0243	0.195**	0.0516	0.0294
	(0.0633)	(0.0846)	(0.0538)	(0.0743)
ΔExchange $rate_{t-1}{}^2$	-0.0972	0.0781	0.00849	0.000712
	(0.126)	(0.0735)	(0.112)	(0.131)
ΔExchange $rate_{t-2}{}^2$	0.0858	-0.0785	0.0457**	-0.0222
	(0.105)	(0.127)	(0.016)	(0.0587)
ΔExchange $rate_{t-3}{}^2$	-0.0788	0.0486	0.061	-0.0517
	(0.0597)	(0.0548)	(0.047)	(0.0289)
ΔExchange $rate_t{}^3$	0.230**	-0.0403	0.0168	-0.104
	(0.0958)	(0.0941)	(0.278)	(0.252)
ΔExchange $rate_{t-1}{}^3$	-0.117	-0.0312	0.0844	0.076
	(0.137)	(0.0683)	(0.289)	(0.509)
ΔExchange $rate_{t-2}{}^3$	0.0724	0.131	0.468	0.155
	(0.102)	(0.0959)	(0.286)	(0.219)
ΔExchange $rate_{t-3}{}^3$	-0.150**	-0.199***	0.540*	0.354
	(0.0714)	(0.0573)	(0.269)	(0.223)
Output gap_t	-0.0121	-0.00761	0.0330*	0.0347*
	(0.0277)	(0.0242)	(0.0148)	(0.0153)
$Inflation_{t-4} \times \Delta$Exchange $rate_t$	0.677	0.955*	1.557	0.825
$=Inflation_{t-4} \times ERPT_t$	(0.504)	(0.549)	(1.226)	(0.608)
$Inflation_{t-4} \times \Delta$Exchange $rate_{t-1}$	0.610**	0.435**	-0.11	-0.235
	(0.234)	(0.187)	(0.564)	(0.711)
$Inflation_{t-4} \times \Delta$Exchange $rate_{t-2}$	0.309*	0.442**	-1.029*	-0.258
	(0.175)	(0.159)	(0.554)	(0.341)

$\text{Inflation}_{t\text{-}4} \times \Delta\text{Exchange rate}_{t\text{-}3}$	-0.0502	-0.00064	0.519	0.453
	(0.0736)	(0.082)	(0.588)	(0.472)
Constant	0.00691	0.00521*	0.00119	0.000551
	(0.00583)	(0.00293)	(0.000968)	(0.0012)
Yearly ERPT	0.119***	0.0841***	0.0167	0.0176**
	(0.0268)	(0.0172)	(0.0093)	(0.00612)
Long-run ERPT	0.276***	0.182***	0.0259	0.0280**
	(0.0708)	(0.0472)	(0.0155)	(0.0113)
$\textit{Inflation}_{t\text{-}4} \times$ *Yearly ERPT*	1.546*	1.831**	0.936	0.784
	(0.787)	(0.759)	(1.314)	(1.131)
$\textit{Inflation}_{t\text{-}4} \times$ *Long-run ERPT*	3.578*	3.969**	1.454	1.248
	(1.283)	(1.113)	(1.895)	(1.639)
Observations	1809	1809	918	834
Countries	22	22	11	10
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Sargan test[a]	0.920	0.775	0.229	0.190
Hansen test[a]	1.000	1.000	1.000	1.000
Serial correlation test[b]	0.636	0.660	0.057	0.067

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.12: Robustness: Different methodologies

Dependent variable: $\text{Inflation}_\text{t}$	Emerging economies			Advanced economies		
	(1)	(2)	(3)	(4)	(5)	(6)
	System GMM	Difference GMM	Within group estimator	System GMM	Difference GMM	Within group estimator
$\text{Inflation}_\text{t-1}$	0.568***	0.482***	0.486***	0.356***	0.153**	0.153**
	(0.0724)	(0.0728)	(0.0715)	(0.0844)	(0.0541)	(0.0539)
$\Delta\text{NEER}_\text{t}$	0.0656***	0.0565***	0.0567***	0.00391	0.00176	0.00176
$=ERPT_t$	(0.0161)	(0.0144)	(0.0141)	(0.00475)	(0.00446)	(0.00445)
$\Delta\text{NEER}_\text{t-1}$	0.0268**	0.0235**	0.0234**	0.0111	0.0136*	0.0136*
	(0.0124)	(0.0112)	(0.011)	(0.00738)	(0.00706)	(0.00704)
$\Delta\text{NEER}_\text{t-2}$	-0.00472	-0.00393	-0.00411	0.00312	0.00927*	0.00927*
	(0.0148)	(0.0138)	(0.0138)	(0.0048)	(0.00512)	(0.0051)
$\Delta\text{NEER}_\text{t-3}$	0.0316**	0.0328***	0.0324**	-0.00142	0.00498	0.00498
	(0.0122)	(0.0116)	(0.0117)	(0.00382)	(0.0029)	(0.00289)
$\Delta\text{NEER}_\text{t}^2$	0.0243	0.00607	0.00636	0.0516	0.00726	0.00726
	(0.0633)	(0.06)	(0.0622)	(0.0538)	(0.0734)	(0.0732)
$\Delta\text{NEER}_\text{t-1}^2$	-0.0972	-0.115	-0.113	0.00849	-0.0332	-0.0332
	(0.126)	(0.119)	(0.12)	(0.112)	(0.0676)	(0.0674)
$\Delta\text{NEER}_\text{t-2}^2$	0.0858	0.0875	0.0893	0.0457**	-0.00779	-0.00779
	(0.105)	(0.0965)	(0.0962)	(0.016)	(0.0295)	(0.0294)
$\Delta\text{NEER}_\text{t-3}^2$	-0.0788	-0.0702	-0.0683	0.061	0.0194	0.0194
	(0.0597)	(0.0585)	(0.0575)	(0.047)	(0.0356)	(0.0355)
$\Delta\text{NEER}_\text{t}^3$	0.230**	0.219**	0.220**	0.0168	-0.486	-0.486
	(0.0958)	(0.0998)	(0.103)	(0.278)	(0.293)	(0.292)
$\Delta\text{NEER}_\text{t-1}^3$	-0.117	-0.11	-0.109	0.0844	-0.369	-0.369
	(0.137)	(0.128)	(0.129)	(0.289)	(0.249)	(0.248)
$\Delta\text{NEER}_\text{t-2}^3$	0.0724	0.0923	0.0945	0.468	0.0786	0.0786
	(0.102)	(0.0967)	(0.0972)	(0.286)	(0.314)	(0.313)
$\Delta\text{NEER}_\text{t-3}^3$	-0.150**	-0.143**	-0.140**	0.540*	0.261	0.261
	(0.0714)	(0.0634)	(0.0626)	(0.269)	(0.248)	(0.247)
$\text{Output gap}_\text{t}$	-0.0121	-0.0152	-0.0158	0.0330*	0.0425*	0.0425*
	(0.0277)	(0.0278)	(0.028)	(0.0148)	(0.0208)	(0.0207)
$\text{Inflation}_\text{t-4}$	0.677	0.7	0.687	1.557	2.503**	2.503**
$\times\Delta\text{NEER}_\text{t}$	(0.504)	(0.497)	(0.489)	(1.226)	(1.1)	(1.096)
$\text{Inflation}_\text{t-4}$	0.610**	0.716***	0.710***	-0.11	0.57	0.57
$\times\Delta\text{NEER}_\text{t-1}$	(0.234)	(0.215)	(0.212)	(0.564)	(0.657)	(0.655)
$\text{Inflation}_\text{t-4}$	0.309*	0.329*	0.324*	-1.029*	-1.044	-1.044

$\times\Delta NEER_{t-2}$	(0.175)	(0.159)	(0.156)	(0.554)	(0.788)	(0.786)
$Inflation_{t-4}$	-0.0502	-0.0533	-0.0516	0.519	0.0358	0.0358
$\times\Delta NEER_{t-3}$	(0.0736)	(0.0717)	(0.0706)	(0.588)	(0.655)	(0.653)
Constant	0.00691	0.00	0.0124***	0.0012	0.00	0.0079***
	(0.005)	(0.000)	(0.003)	(0.001)	(0.000)	(0.001)
Yearly ERPT	0.119***	0.109***	0.108***	0.0167	0.0296***	0.0296***
	(0.0268)	(0.0234)	(0.023)	(0.0093)	(0.00806)	(0.00804)
LR ERPT	0.276***	0.210***	0.211***	0.0259	0.0350***	0.0350***
	(0.0708)	(0.049)	(0.0481)	(0.0155)	(0.0106)	(0.0105)
$Inflation_{t-4}$	1.546*	1.692**	1.670**	0.936	2.065	2.065
$\times$ *Yearly ERPT*	(0.787)	(0.755)	(0.739)	(1.314)	(1.34)	(1.336)
$Inflation_{t-4}$	3.578*	3.265**	3.247**	1.454	2.438	2.438
$\times$ *LR ERPT*	(1.283)	(1.062)	(1.049)	(1.895)	(1.485)	(1.48)
Observations	1809	1787	1809	918	907	918
Countries	22	22	22	11	11	11
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sargan test[a]	0.920	0.604		0.229	0.011	
Hansen test[a]	1.000	1.000		1.000	1.000	
Serial correlation[b]	0.636	0.705		0.057	0.251	
Within R^2			0.814			0.467

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Table 4.13: Robustness: GMM with different lag structures

Dependent variable: Inflation_{t}				
	Emerging economies			
	(1)	(2)	(3)	(4)
	System GMM: instruments: 2–8 lags	System GMM: instruments: 2–7 lags	System GMM: instruments: 2–6 lags	System GMM: instruments: 2–5 lags
$\text{Inflation}_{t\text{-}1}$	0.568***	0.568***	0.566***	0.562***
	(0.0724)	(0.0724)	(0.0724)	(0.0736)
ΔNEER_{t}	0.0656***	0.0655***	0.0667***	0.0682***
$=ERPT_t$	(0.0161)	(0.0162)	(0.0159)	(0.016)
$\Delta\text{NEER}_{t\text{-}1}$	0.0268**	0.0268**	0.0273**	0.0254*
	(0.0124)	(0.0124)	(0.0123)	(0.0128)
$\Delta\text{NEER}_{t\text{-}2}$	-0.00472	-0.00472	-0.0038	-0.00474
	(0.0148)	(0.0148)	(0.0149)	(0.0152)
$\Delta\text{NEER}_{t\text{-}3}$	0.0316**	0.0316**	0.0318**	0.0312**
	(0.0122)	(0.0122)	(0.0122)	(0.0121)
$\Delta\text{NEER}_{t}{}^{2}$	0.0243	0.0241	0.0358	0.0243
	(0.0633)	(0.0634)	(0.0676)	(0.0689)
$\Delta\text{NEER}_{t\text{-}1}{}^{2}$	-0.0972	-0.0971	-0.106	-0.113
	(0.126)	(0.126)	(0.128)	(0.131)
$\Delta\text{NEER}_{t\text{-}2}{}^{2}$	0.0858	0.0858	0.0887	0.0886
	(0.105)	(0.105)	(0.106)	(0.108)
$\Delta\text{NEER}_{t\text{-}3}{}^{2}$	-0.0788	-0.0788	-0.083	-0.0847
	(0.0597)	(0.0597)	(0.0605)	(0.0635)
$\Delta\text{NEER}_{t}{}^{3}$	0.230**	0.230**	0.242**	0.226**
	(0.0958)	(0.0958)	(0.1)	(0.101)
$\Delta\text{NEER}_{t\text{-}1}{}^{3}$	-0.117	-0.117	-0.128	-0.135
	(0.137)	(0.137)	(0.141)	(0.143)
$\Delta\text{NEER}_{t\text{-}2}{}^{3}$	0.0724	0.0724	0.074	0.0763
	(0.102)	(0.102)	(0.104)	(0.106)
$\Delta\text{NEER}_{t\text{-}3}{}^{3}$	-0.150**	-0.150**	-0.153**	-0.157**
	(0.0714)	(0.0714)	(0.0709)	(0.0729)
Output gap_{t}	-0.0121	-0.0119	-0.00606	-0.0116
	(0.0277)	(0.0277)	(0.0254)	(0.0274)
$\text{Inflation}_{t\text{-}4}$	0.677	0.677	0.662	0.657
$\times\Delta\text{NEER}_{t}$	(0.504)	(0.504)	(0.507)	(0.507)
$\text{Inflation}_{t\text{-}4}$	0.610**	0.610**	0.616**	0.632**
$\times\Delta\text{NEER}_{t\text{-}1}$	(0.234)	(0.234)	(0.234)	(0.238)
$\text{Inflation}_{t\text{-}4}$	0.309*	0.310*	0.307*	0.313*

$\times\Delta NEER_{t\text{-}2}$	(0.175)	(0.175)	(0.175)	(0.177)
$Inflation_{t\text{-}4}$	-0.0502	-0.0502	-0.0497	-0.0476
$\times\Delta NEER_{t\text{-}3}$	(0.0736)	(0.0736)	(0.0736)	(0.0734)
Constant	0.00691	0.00219	0.00147	0.00148
	(0.00583)	(0.00495)	(0.00215)	(0.00215)
Yearly ERPT	0.119***	0.119***	0.122***	0.120***
	(0.0268)	(0.0268)	(0.0271)	(0.0285)
Long-run ERPT	0.276***	0.276***	0.281***	0.274***
	(0.0708)	(0.0708)	(0.0702)	(0.0728)
$Inflation_{t\text{-}4}$	1.546*	1.546*	1.536*	1.554*
×*Yearly ERPT*	(0.787)	(0.787)	(0.785)	(0.791)
$Inflation_{t\text{-}4}$	3.578*	3.579*	3.539*	3.548*
×*Long-run ERPT*	(1.283)	(1.283)	(1.277)	(1.271)
Observations	1809	1809	1809	1809
Countries	22	22	22	22
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Sargan test[a]	0.920	0.917	0.170	0.000
Hansen test[a]	1.000	1.000	1.000	1.000
Serial correlation [b]	0.636	0.636	0.637	0.647

Pass-through coefficients, based on Equation 4.3. System GMM estimation using Arellano & Bover (1995) and Blundell & Bond (1998) dynamic panel estimator. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Reports p-values for the null hypothesis that the instruments used are not correlated with the residuals.

[b] Reports p-values for the null hypothesis that the errors in the first difference regression exhibit no second order serial correlation.

Appendix D: Heterogeneity across EMEs

This appendix discusses possible heterogeneity in pass-through trends across EMEs. This appendix closely relates to an accompanying paper Arslan *et al.* (2016).

While our main results in Essay 3 should be read as broad, cross-country trends which might provide guidance for all EMEs, in Arslan *et al.* (2016), we additionally discuss changes in exchange rate pass-through by comparing our panel data estimates with a questionnaire responses across these emerging market economies (Table 4.14).

The results of questionnaire responses are broadly consistent with the panel estimates. Ten EMEs found weakening pass-through and only two a strengthening one, five respondents saw no change (Table 4.14). These results also imply that EME experiences are likely to be heterogeneous to some extend.

Figure 4.7: Pass-through heterogeneity:[1] contemporaneous exchange rate pass-through[2]

[Figure here]

[1]The country composition of groups is listed in Table 4.15. [2]Given that all three measures of pass-through show similar trends, here we focus on contemporaneous pass-through for expositional clarity. [3] Q1 2001–Q2 2008. [4]Q3 2009–Q2 2013

As a result, we repeated the analysis for sub-samples, EMEs with free-floating exchange rates, inflation targeting regimes or large shares of commodity exports or focusing on more compact the geographic regions such as Asia or Latin America. These results suggest that the main trend of declining pass-through is present broadly among EMEs (all estimates with the exception of Asia are below the 45 degree line in Figure 4.7.

Table 4.14: Questionnaire responses

Country	In the post-2008 period, did exchange rate pass-through...		
	...weaken?	...remain stable?	...strengthen?
Algeria			
Argentina			
Brazil			
Chile		X	
China	X		
Colombia		X	
Czech Republic		X	
Hong Kong SAR			
Hungary	X		
India	X		
Indonesia	X		
Israel	X[a]		
Korea	X[b]		
Malaysia		X	
Mexico	X		
Peru			X
Philippines	X[c]		
Poland	X		
Russia			X
Saudi Arabia		X[d]	
Singapore			
South Africa	X		
Thailand	X		
Turkey		X	
United Arab Emirates			

[a]This was mainly due to a drop in dollar indexation of housing in 2007.
[b]Estimation results based on various empirical models suggest that exchange rate pass-through declined in the post-2008 period.
[c]Exchange rate pass-through in the post-2008 period weakened; coefficient declined from 0.07 (ie in 2002–08) to -0.15 (i.e. from 2009 to Q2 2015).
[d]Indirect pass-through.

Source: Arslan *et al.* (2016)

Of course, some differences remain. For instance, freely-floating exchange rate regimes have seen a larger than average fall in pass-through while Asian economies seem to be countering general trends.

Nonetheless, these smaller country group estimates should be treated cautiously as the estimates are becoming less stable as we shrink the sample size.

Table 4.15: Emerging market economies grouping

Country	Inflation	Commodity	Freely	Weaker	Latin	Asia	Other
Country	targeters	exporters	floating	ERPT (survey)	America	regions	
Algeria							X
Argentina		X			X		
Brazil	X	X	X		X		
Chile	X	X	X		X		
China				X		X	
Colombia	X	X			X		
Czech Republic	X		X				X
Hong Kong						X	
Hungary	X		X	X			X
India				X		X	
Indonesia	X	X		X		X	
Israel	X		X	X			X
Korea	X		X	X		X	
Malaysia						X	
Mexico	X		X	X	X		
Peru	X	X			X		
Philippines	X		X	X		X	
Poland	X		X	X			X
Russia	X	X					X
Saudi Arabia							X
Singapore						X	
South Africa		X		X			X
Thailand	X			X		X	
Turkey	X		X				X
United Arab Emirates							X

Sources: Arslan *et al.* (2016),IMF, UN Comtrade; national data

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Appendix: Report response to opponents

I would like to thank all referees for their invaluable comments and suggestions in their referee reports as well as during the pre-defense. I have organized responses by chapters and hereby I also provide short answers and references to the specific sections of the dissertation.

General comments

It would be helpful to harmonize the style of Introduction with that of the individual essays...)
Another suggestion would be to make a brief overall assessment of the three essays and link them to teach other. Perhaps Martina could add a couple of paragraphs or a page to jointly assess the essays and discuss the lessons learned.
The introductory section has been rewritten to accommodate all of the proposed changes and provide better motivation for the essays.

Paper 1

Table 2.1 presents policy responses adopted by central banks in the CEE region during 2003–2008. For the Czech Republic, Table 2.1 does not list any measure. It would be worth adding a comment on the Czech case, e.g. explaining why there was no measures – because credit growth was not an issue, or due to other reasons?
We do not report any measure for the Czech Republic as the survey response from the Czech National Bank indicated that no measure has been explicitly taken to curb the credit growth in the period 2003–2008. This comment as been added to the footnote 6 on the page 18.

Relatedly, it would be very useful to add a line to Table 2.1 showing the average credit growth during 2003–2008 for each of the listed countries. Eventually, is it possible to see a correlation between the credit growth and the measures adopted (either the number of measures or their overall duration)?
Information on an average credit growth has been added to Table 2.1 as suggested. The data suggests that, as expected, there is a positive correlation (coefficient 0.6) between the frequency of policy actions and credit growth. An additional discussion has been added to the main text (page 20).

Since the effect of policy measures is the central question, I feel there should be more discussion of the issue of endogeneity – bi-directional relationship between the development of credit growth and policy actions. Indeed, as it is correctly mentioned in the essay, policy measures are likely to be adopted in reaction to rapidly raising credit, while the main empirical specification contains the credit growth as the dependent variable and policy measures as explanatory variables. As the solution to endogeneity, policy measures are lagged by one period, i.e. by one month. Is one month enough? It would be useful to add a footnote commenting on a pass-through from policy measures to credit growth and explaining the lag selection.

In Appendix C (Table 2.6), I have included results for different specification of lag structures of the policy actions (from 1 to 3 month lags). The results remain robust to these baseline findings.

As an alternative solution to endogeneity, GMM is mentioned (footnote 12 on p. 26). It is unclear why the GMM estimator was not used, while it was adopted in the study the authors refer to. Besides, in the third essay, the GMM estimator is used to deal with endogeneity; the data sample is of comparable size. So the reader might wonder why the lagged values are used to address endogeneity in the first essay, while the GMM is applied to address the same type of problem in the third essay.

I have replaced the benchmark methodology with dynamic panel GMM. In the updated version, the baseline version hence uses 1-12 lags of credit growth and policy dummies as GMM instruments for first difference equations. I have repeated our calculations for different structure of lagged instruments as well as within group estimator and the results stay robust to the benchmark. The GMM results are now provided in the main text Tables 2.3 and 2.4 and I have moved the original within group estimates to the Appendix C Table 2.7.

It could be also discussed how exactly the Czech Republic is included into panel regressions with policy variables (equations 2.1 and 2.2), given that according to table 2.1 there was no policy measures adopted in the Czech Republic. How sensitive are the results to the presence of the Czech Republic in the regressions?

The Czech Republic is included in the regressions as a control country – in all periods the dummies for policy actions are reported as 0. I have also prepared new results excluding the Czech Republic. These results are reported in Appendix C Tables 2.8 and 2.9 and they remain robust to the benchmark.

The choice of macroeconomic control variables could be further discussed. For example, why interest rates was used in levels instead of differences?
Generally, the aim is to include main controls which are widely available for all EMEs over the full period. I have also have added a robustness results on interest rate changes (as opposed to levels) to the Appendix C Table 2.7 and the results remain similar to the specification with levels.

What are the policy recommendations for the current situation? Could the results of the 2003–2007 credit expansion be used to address current challenges? How do the findings matter for current and future policy making? (e.g., are there any relevant recommendations how current tools used by CEEs could be amended/altered; are the findings in this study likely to also hold in the future and/or in other regions of the world and why)
What could be future issues to be looked at?
I have added a full new subsection to address policy recommendations into the Introduction of the thesis. Additionally, I have also implemented small changes with references to the conclusion of essay 1, as suggested.

Paper 2

While the essay focuses on banking crises in emerging countries, it could be also commented on other types of crisis and on their interaction, that is how one type of crisis triggers (affects) the other. Indeed, for the Emerging market countries in particular, there exists a numerous literature investigating the twin crises and crisis interaction.
This discussion has been added to the main text of the essay (page 46).

Notice that the period under review – especially the end of the sample – includes also the numerous episodes of the sovereign debt crisis (although more related to the developed countries). Do the authors see any implications for their results, e.g. via spillovers?
Six out of 14 analyzed crises start in 2008 (see Appendix B). The majority of these episodes fall into the region of Europe which can in line with a concern of picking up a more-widely rooted sovereign debt crisis. Nonetheless, when zooming on the region of emerging Europe, we also find higher magnitudes

on AUC coefficients for a number of credit-based EWIs than in the full sample (Section 3.5.5.). Although spillovers can be a concern, the results suggest that the credit variables can be still useful in picking up the future banking distress. I have also added short discussion into the section 3.5.5.

According to Table 3.10, the Czech Republic experienced a banking crisis during 1996Q1–2000Q4 (the coding is taken from Laeven and Valencia, 2012). It would be useful to add a comment whether this coding is in accordance with the authoŕs economic intuition (and with the view of the local experts – see, for example, the Financial Stability Reports by the Czech National Bank). This could be also used for a brief discussion whether a set of uniformly applied statistical measures could distinguish the episodes of genuine banking crises from the episodes of e.g. privatization and restructuring.
I have incorporated this discussion to subsection 3.3.1 Definition of the crisis. Additionally, robustness section now includes analysis against alternative credit database (Babecký *et al.* (2014)).

Since the essay focuses on banking crises, the measurement issue – how banking crises are defined – would deserve more discussion. Given that the definition of banking crises is not unique (especially the end of the crisis), robustness assessment is welcomed.
An additional discussion and robustness assessment has been added. Please see subsection 3.3.1 "Definition of the crisis" and 3.5. "Robustness".

I would suggest to consider splitting of the sample based on homogeneous regions or stage of development as additional robustness check to see how those parameters could change in the conclusion.
Robustness against more homogeneous regions has been added (see subsection 3.5.5. "More homogeneous country groupings").

The AUCs for DSR growth in Table 3.3 appear high based on Figure 3.24 – and are probably driven by the limited sample of EMEs crises covered. While this is stressed a general caveat, the author could explain briefly why she believes that this ratio still seems to work well.
As a part of the revision process, we have removed debt-service ratio and we now exclusively focus on credit-based early warning indicators. This shift has been explained in the motivation on the essay 2.

The use of real time filters is challenging and has a strong bearing on the usefulness of credit-to-GDP gap ratios. The pragmatic approach chosen in this

study (in line with BCBS 2010 and Drehmann/Juselius 2014) is a useful starting point, but the author might want to stress that more work is needed in this area to avoid compromising the use of deviations from long-term trends (such as gaps) for early warning purposes in EMEs as credit growth patterns could become more similar as in advanced economies going forward.
We have added a discussion to the main text. Also, we have added additional discussion and results on different constructions of credit-to-GDP gaps (i.e. smoothing parameters) to the Robustness section.

Paper 3

It might be also interesting to investigate whether results remain the same in case of more homogeneous sample of emerging markets – e.g. Europe, Latin America, South-East Asia etc.
A new Appendix D has been added to address heterogeneity across the EME sample. Appendix D also discusses a possible split into a more homogeneous groups both geographically (e.g. Asia, Latin America) and in terms of key characteristics (e.g. inflation targeters, freely-floating exchange rate regime). The results show that the main patterns of the ERPT broadly hold also for a majority of more homogeneous sub-samples. Nonetheless, the smaller country group results should be treated cautiously as these GMM estimates are becoming less stable with smaller panels.

In response to the discussion of possible asymmetries during the pre-defense, I have also added a footnote 5 on the page 80–81 to motivate the choice of our specification.