DISS. ETH NO. 28057

Interactions of Financial Crises with the Economy and the Role of Macroprudential Policies

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH
(Dr. sc. ETH Zurich)

presented by

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2021

Acknowledgments

I would like to thank my supervisor, Professor Jan-Egbert Sturm, for giving me the opportunity to conduct this dissertation at the Chair of Applied Macroeconomics. It has been a life changing opportunity for me. I thank him for his support throughout the process and for being a very supporting and open-minded co-author, always ready to acknowledge my ideas and help steer them in the right direction. I would also like to thank my co-examiner, Professor Steven Ongena for taking the time to review this dissertation, but also for his kind support at several points throughout my PhD when I reached out for help. I gratefully acknowledge the financial support from the Swiss Confederation through the ESKAS Scholarship scheme.

Special thanks goes to Marco Gross, my co-author and former mentor during my internship at the IMF, for his generous support throughout and beyond the internship and our joint project. I would also like to thank Stefan Pichler who over the past year became my go to person for advice always when I needed to resolve an immediate doubt, helping me progress through my projects faster. Thanks to my co-authors Sebastian Dörr and Philipp Schaz who have kindly taken me on board for a joint project in the early stage of my PhD, from whom I have learned a lot. Thanks to Daniel, Andrin, Regina, Sina, Simon, Jan, Florian, Pepe, Michael, Stephan, Aranya, Sebastian, Florian, Filippo and Lamar for the many fruitful exchanges and for giving me a hand always when I needed it. Thanks to Giulio for helping with the Italian translation of the abstract. I am grateful to my friends Maja, Nina and Jelena for going through the many breakdowns with me. Last but not least, I thank my mother for the unconditional love and support throughout my whole life. This is an achievement of us both.

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Abstract

This dissertation is a collection of four essays on financial crises and macroprudential regulation and policies. Each of them addresses financial (in)stability from different aspects and proposes potential methodological improvements of policy tools.

The first chapter (co-authored with Jan-Egbert Sturm) analyzes whether governments turn to policies that restrict the openness of their economies as a reaction to financial distress situations. In answering the research question, we focus on currency crises, which are most directly linked to imbalances in the external sector. We find that currency crises lead to a decline in the de jure globalisation index, driven by a decrease in financial de jure globalization. The financial openness of a country decreases in the 5-year period after the currency crisis through two channels: First, the country slows down on its capital account liberalization, indicating that capital controls and similar barriers remain in place for a prolonged period after the crisis. Second, in order to preserve space for future use of these barriers, the countries engage in half as many international investment agreements.

In the second chapter (co-authored with Sebastian Dörr and Philipp Schaz) we examine whether bank industry specialization determines how banks transmit funding shocks during banking crises to borrowers and how these shocks spill over to non-crisis countries. We show that during banking crises, higher industry specialization leads to banks maintaining higher loan growth to industries and firms at the intensive margin. The impact of specialization on lending to all firms within a specialized industry becomes significant 6 months after the shock. To support their liquidity needs in the country experiencing the crisis, banks withdraw funding from connected, non-affected countries. However, they insulate their main industries

from this effect - banks with one standard deviation higher industry specialization entirely offsets the negative spillover effect to those industries. Our findings suggest that bank industry specialization plays a role in banks' response to financial shocks and their transmission across markets.

Bank regulation has been successful in reducing the systemic risk, but has often constrained banks' profitability and lending potential, opening the space for institutional lenders to partially substitute banks in meeting the loan demand in the market. The third chapter examines whether tighter liquidity regulation affects the credit allocation between banks and institutional lenders in the syndicated loan market. For identification, it exploits heterogeneous timing of implementation of liquidity requirements across countries and corporate loan-level data from the syndicated loan market since 2010. The evidence shows that, following the liquidity tightening, institutional tranches expand by 28%. However, this paper finds no evidence that banks decrease lending in response to the policy introduction. Therefore, instead of substitution it proposes alternative explanations for these findings.

In the forth chapter (co-authored with Marco Gross), motivated by the need for obtaining econometric models with theory-conform signs of long-run multipliers or other groups of covariates for the purpose of financial stress testing, we implement a vector-sign-constrained variant of existing model shrinkage methodologies, such as (Adaptive) Lasso and (Adaptive) Elastic Net. We illustrate that the addition of vector-constraints "helps the Oracle property" for those methods that do not initially carry it, while for methods that do possess it already, the vector constraints help increase efficiency (precision) in small samples, conditional on the constraints being in line with a true data generating process. Extensive numerical experiments show that our method performs better than their unconstrained counterparts, while the application to the real dataset highlights their importance in economic modelling and prediction.

Riepilogo

Questa tesi è una raccolta di quattro saggi su crisi finanziarie e politiche macroprudenziali. Ciascuno di essi affronta la (in)stabilità finanziaria da diversi punti di vista e propone potenziali miglioramenti metodologici degli strumenti di politica pubblica.

Il primo capitolo (scritto in collaborazione con Jan-Egbert Sturm) analizza se i governi ricorrono a politiche che limitano l'apertura delle loro economie in reazione a situazioni di difficoltà finanziaria. Ci concentriamo sulle crisi valutarie, che sono più direttamente collegate agli squilibri nel settore estero. Dimostriamo che le crisi valutarie portano a un calo dell'indice di globalizzazione de jure, guidato da una diminuzione della globalizzazione finanziaria de jure. L'apertura finanziaria di un paese diminuisce nei cinque anni succesivi ad una crisi valutaria attraverso due canali: in primo luogo, il paese rallenta la liberalizzazione del suo conto capitale, indicando che i controlli sui capitali rimangono in vigore per un periodo prolungato dopo la crisi. In secondo luogo, al fine di preservare lo spazio per l'utilizzo di queste barriere, i paesi si impegnano in accordi di investimento internazionali con frequenza due volte minore.

Nel secondo capitolo (scritto in collaborazione con Sebastian Dörr e Philipp Schaz) esaminiamo se la specializzazione delle banche determina il modo in cui, durante le crisi bancarie, le banche trasmettono gli shock di finanziamento ai mutuatari e come tali shocks si estendono nei paesi senza crisi. Dimostriamo che durante crisi bancarie una maggiore specializzazione del settore porta le banche a mantenere una maggiore crescita dei prestiti alle imprese nel margine intensivo. L'impatto della specializzazione sui prestiti a tutte le imprese all'interno di un settore specializzato

diventa significativo 6 mesi dopo lo shock. Per sostenere le loro esigenze di liquidità nel paese in crisi, le banche ritirano i finanziamenti da paesi collegati que non stanno attravesando una crisi. Tuttavia, isolano le loro industrie principali da questo effetto: le banche con una deviazione standard di maggiore specializzazione del settore compensano interamente l'effetto di ricaduta negativo su tali industrie. I nostri risultati suggeriscono che la specializzazione settoriale svolge un ruolo nella risposta delle banche agli shock finanziari e nella loro trasmissione attraverso i mercati.

La regolamentazione bancaria ha avuto successo nell'affrontare il rischio sistemico, ma ha spesso limitato la redditività e il potenziale di prestito delle banche, consentendo ai prestatori istituzionali di sostituire parzialmente le banche nel soddisfare la domanda di prestito sul mercato. Il terzo capitolo esamina se una regolamentazione più severa sulla liquidità influisce sull'allocazione del credito tra banche e prestatori istituzionali nel mercato dei prestiti sindacati. L'evidenza mostra che, a seguito della stretta di liquidità, le tranche istituzionali si espandono del 28%. Tuttavia, questo articolo non trova prove che le banche riducono i prestiti in risposta all'introduzione della politica, quindi, invece della sostituzione, propone spiegazioni alternative per spiegare effetto trovato.

Nel quarto capitolo (scritto in collaborazione con Marco Gross), motivato dalla necessità di ottenere modelli econometrici con segni conformi alla teoria di moltiplicatori di lungo periodo o altri gruppi di covariate per lo stress test finanziario, implementiamo una variante vincolata al segno vettoriale delle metodologie di restringimento del modello esistenti, come (Adaptive) Lasso e (Adaptive) Elastic Net. Illustriamo che l'aggiunta dei vincoli del vettore "aiuta la proprietà Oracle" per quei metodi che inizialmente non lo portano, mentre per i metodi che lo possiedono già, i vincoli del vettore aiutano ad aumentare l'efficienza (precisione) in piccoli campioni, a condizione que i vincoli siano in linea con un vero processo di generazione dei dati. Esperimenti numerici estesi mostrano che il nostro metodo funziona meglio delle loro controparti non vincolate, mentre l'applicazione al set di dati reale evidenzia la loro importanza in modelli e previsioni economiche.

Introduction

There has been an extraordinary range of financial crises in history. They differ in their characteristics, affect both rich and poor countries and severely worsen economic outcomes. Financial crises often lead to depression of consumption, investment and economic activity, leading to a loss of output and rise in unemployment. The negative effects often persist and evidence shows that countries typically struggle to get back on their pre-crisis growth path trajectories.

Financial crises can have domestic or external origins, and stem from private or public sectors. If there is one common theme, it is that excessive debt accumulation, whether it be by the government, banks, corporations, or consumers, often poses greater systemic risks than it seems during a boom (Rogoff et al., 2013). Despite the wide variety of factors playing a role in each crisis, the literature broadly divides them into three types of crises: sovereign defaults, banking crises and currency crises. Sovereign debt crises happen when governments fail to meet payments on its external or domestic debt obligations, and have to default on or restructure their debt. Banking crises are characterized by liquidity shortages, losses in the banking system and often bank runs. As banks come under severe stress, they become unable to provide lending to firms and households, leading to a contraction of aggregate demand. The third type of crises are currency crises, characterized by a sharp depreciation of a domestic currency due to the inability of the government to maintain a fixed exchange rate, often accompanied by a speculative attack.

In addition, all these crises have a tendency to spill over across borders. This is increasingly the case as a result of growing integration of financial markets. The Global Financial Crisis (GFC) in 2008 seriously called into question the costs and benefit of financial globalization, which to a certain extent amplified the spillovers from the U.S. to the connected financial markets and ultimately across the whole world. This event has, in turn, potentially led to a change in sentiment towards globalization as a beneficial economic phenomenon. The first chapter of this thesis investigates whether currency crises, throughout recent history, led to a decrease in globalization-supporting policies. We find that there is a decrease in de jure globalization in the 5-year period after the crisis, caused by a prolonged use of capital controls and fewer incentives to enter international investment agreements. As foreign investments represent an important factor of growth in developing countries, such findings could imply a negative impact to the growth prospects of affected countries.

The impairment of growth that comes from decreased economic activity caused by any type of crises, can come through various channels. In the case of banking crises, the shock is transmitted through the financial system and banks' inability to maintain pre-crisis lending volume. The second chapter focuses on banking crises and evaluates their impact on bank lending volume, focusing on the role of bank portfolio specialization. It examines whether bank industry specialization determines how banks transmit funding shocks to borrowers and how they spill over to non-crisis countries. Industry specific information can play a crucial role in banks screening of their borrowers during periods of financial distress. In addition, banks might be incentivized to preserve the relationship with firms in their specialized industries in order to maintain the valuable sector-specific knowledge for the post-crisis period. We find that banks shield their relationship firms within their dominant industries during the crisis, extending that support to entire industries 6 months following a crises. At the same time, in order to support their liquidity needs in a country experiencing the crisis, banks withdraw funding from non-affected countries, but shield their specialized industries from this negative spillover effect.

While it is helpful to understand different distributional concern in the crises aftermath, the economy inevitably suffers when experiencing financial crises. Therefore, it is one of the main goals of macroeconomic policy to avoid crises occurrence and maintain the stability of the system. Following the GFC, there has been an increased effort of policy-makers to design and improve policies aimed at reducing the systemic risk in the financial markets, hoping to learn from this experience and prevent similar events from happening in the future. Banking supervision dates back to the 1980s when the first regulatory framework was proposed, known as the Basel I Accord. The Basel Accords were formed with the goal of creating an international regulatory framework for managing credit and market risk. Their key function is to ensure that banks hold enough capital to meet their financial obligations and survive in financial and economic distress. They also aim to strengthen corporate governance, risk management, and transparency. The framework evolved over time, with Basel III emerging after the GFC being the most comprehensive and addressing the shortcomings identified in financial supervision following the recent crisis.

While regulation helps minimize identified risks in the economic system, the market participants will always try to find a way to circumvent the regulation. In the current financial landscape, the circumvention of macroprudential policies comes from an increased participation of the so far unregulated non-deposit taking lending institutions, known as non-banks or institutional lenders. These institutions include investment funds, insurance firms, mutual funds, pension funds, etc. The third chapter of this thesis looks at such substitution of bank with non-bank lending in response to the tightening of liquidity requirements imposed on banks. As liquidity tightening impairs credit growth and consumption less often than, for instance, tightening of credit regulation, the evidence shows that there is no actual reduction of bank lending. However, non-bank lending does react to the introduction of liquidity regulation, arguably due to the general equilibrium effects of policy-induced rise in liquidity of non-banks' collateral.

Finally, one important component of the modern macroprudential framework is the regular use of financial sector stress tests by financial institutions and those who supervise them, in order to assess the robustness of the financial system and gauging risks arising at a system-wide level. The process of stress testing involves selecting the models that are used to establish a link between risk parameters with the macro and financial factors defined in a scenario, to thereby project the evolution of the market risk conditional on a scenario. The future paths of these variables are embedded in the scenarios used to conduct a forward-looking simulation of the evolution of the variables measuring systemic risk in the financial system. Having a reliable model selection methodology to disseminate model uncertainty inherent in so-called "hand-picked models" – those subject to the discretion of the researcher – is of great importance in financial stress testing and economic forecasting in general. The fourth chapter of this dissertation is a methodological contribution to such model selection procedures. We augment the four model selection methods- (adaptive) LASSO and (adaptive) Elastic Net to allow for inclusion of prior economic knowledge through imposition of sign constraints. Having a theoretically sound relationship between predicted variable and its regressors is crucial for meaningful predictions.

Studying the effects of financial crises and tailoring appropriate policies for their prevention and management is an important mandate of macroeconomic policy, as it can make a significant difference in their impact on the economy and help prevent major disruptions. The latest economic crisis caused by the corona virus pandemic is an example of successful reactions by fiscal and monetary policy authorities. Although the world has suffered a serious economic crisis, the financial markets remained stable – in part thanks to the evolution of banking regulation over the last decade that led banks to have enough buffers to withstand the economic shock, in part thanks to the appropriate policy reaction that provided enough liquidity to the markets to prevent their freezing.

This dissertation aims to contribute to the creation and fine-tuning of such policies by casting light at the effects of financial crises from the perspective of different types of crises and different actors, as well as by analyzing the role of existing regulation and suggesting potential methodological improvements to the existing macroprudential toolkit.

Chapter 1

Currency Crises and Globalisation Policies[1]

1.1 Introduction

Currency crises, also knows as balance of payment crises, are among the most disruptive events in an economy. They are characterized by sharp depreciations of the local currency in the foreign exchange market. The countries with higher current account deficits, levels of dollarization and a large shares of foreign currency inflow are more susceptible to a balance of payment crisis (Chernyak et al., 2013).

The current account deficit implies that the country imports more than it exports, leading to an increased supply of a nation's currency in the foreign exchange markets, which puts a depreciative pressure on the exchange rate. To maintain a

[1]This chapter is based on Boskovic and Sturm (2021)

fixed exchange rate, the central bank has to intervene in the foreign exchange market to support the value of the currency, thus depleting the country's stock of foreign reserves. When the ability of a central bank to maintain the fixed exchange rate is questioned, speculative attacks may occur, leading to a currency crisis. Many countries resort to tariff increases when they face external deficits (Roldos, 1991). Although this partial equilibrium view only considers reduction in imports, ignoring other adjustments in the economy, policy makers might try to achieve greater stability of the currency by imposing barriers on imports.

In a similar vein, when faced with a balance of payment problems, policy-makers might resort to imposing barriers to the capital account of the balance of payments. Such prohibitions on capital account transactions include measures aimed to discourage capital outflows from the country or limit short-term capital inflows that can easily be reversed. History has recorded several cases where countries limited their international capital flows, with the hope of insulating economies from speculative attacks and thereby creating greater currency stability (Glick and Hutchinson, 2005). This has been the case with numerous currency crises, including Spain during the European currency turmoil of the fall of 1992, as well as Malaysia and Thailand in the context of the Asian financial crisis of 1997-99 (Otker et al., 2000). In a more recent example, during the Global Financial Crisis, nations like Iceland, Indonesia, the Russian Federation, Argentina and Ukraine put capital controls on outflows of capital to "stop the bleeding" related to the crisis (Gallagher, 2011).

While there are many examples of the use of capital controls and trade barriers to cope with the immediate balance of payment imbalances and financial crises, our paper focuses on the question whether there is a lasting shift in globalization sentiment reflected in the deceleration of globalization supporting policies in the five-year period following a currency crisis. Investigation is motivated by the fact that, more than any other economic crisis, currency crises closely relate to the level of openness to the rest of the world. With the increase in globalization, both international trade and cross-border capital flows have seen a tremendous increase, providing a link between the level of globalization and balance of payments imbalances that could potentially lead to crises. In addition, these crisis episodes are in many cases triggered by speculative attacks in foreign exchange markets, where the speculators are usually perceived as external, coming from outside of the country. These considerations suggest that, after experiencing a currency crisis, policy makers are potentially more prone to change the sentiment towards international integration, and favour protectionist anti-globalization policies. Indeed, some economists believe that there is a trade-off between financial stability and the benefits from global integration. Greenspan (2001), for instance, suggests that retaining the controls to limit foreign-currency debt and potential capital flight would make the economy less prone to financial crises, pointing out the fact that India and China, with their extensive capital controls at the time, avoided major distress during the Asian financial crisis. If there is a tradeoff between stability and integration, the policy choice between the two must reflect the preference of the policy makers of one over the other, and it would not be surprising that their preferences move further away from globalization after having experienced a balance of payment crisis.

We test this hypothesis by estimating the impact of currency crises on policies and conditions that enable, facilitate, and foster international flows and activities, as measured by the KOF de jure Globalization Index. We focus on the economic part of the index, i.e. de jure financial globalization and de jure trade globalization. One way to avoid the expansion of current account deficits is to introduce restrictions on imports, such as different trade regulations, tariffs or quotas. Countries may even be inclined to enter less trade agreements in order to be able to exercise the protectionist policies in the future. These dimensions are reflected in the subdimension de jure trade globalization. We look into the medium-term effect of currency crisis on de jure trade globalization sub-index to investigate whether countries resort to, and persist in maintaining such measures in the five-year period after the crises. If the balance of payment imbalances come from volatile capital flows and risks related to the capital account, policy makers might resort to a range of controls on inflows or outflows of capital, which are reflected by the de jure financial globalization sub-index. Similarly, to the de jure trade sub-index, the sub-index captures the number of bilateral investment agreements in addition to the capital controls and investment restrictions.

On a more granular level, we test the effect of currency crises on the subcomponents of the two relevant sub-indices, to assess what particular policy changes generate a potential deceleration in de jure globalization index. We argue that such impact may come through two different channels captured by respective sub-indices. One potential way is through longer-term imposition or retention of trade and capital barriers. However, we argue that the negative impact of crises on de jure globalization could also be related to the decline in trade and investment bilateral agreements, in order to reserve space for exercising protections policies. Gallagher

(2011) analyses the case of the United States and finds that the trade and investment agreements leave little room to manoeuvre when it comes to capital controls. This implies that if a country wants to shift toward protections policies in the future, they will have to distance themselves from these investment agreements to a certain degree. Therefore, we test additional hypotheses: The countries maintain financial/trade barriers in the prolonged period after the currency crisis; and: The countries enter less free trade and/or bilateral investment agreements to preserve space for future use of protectionist policies.

We use data from a wide historical range of currency crises, covering the period between 1970 and 2017, looking at 203 countries. To assess the mid-term impact and make sure that we are not only measuring short-term volatility we aggregate the data into 5-year averages prior to the analysis. Based on obtained coefficients and autoregressive lag of the dependent variable, we calculate the long-term impact of the currency crisis on dependent variable. To estimate the model we use fixed effect regression and system Generalized Method of Moments (GMM). We find that the currency crises are indeed associated with a decrease in the KOF de jure Globalization index. When looking into the de jure financial and trade subindices individually, we only find an impact on de jure financial globalization. We then test whether this impact is driven by the decrease of capital account openness, a decline in the number of international investment agreements, or both. We find that the occurrence of currency crisis undoes the positive trend in capital account liberalization in the five-year post-crisis period. We also find a negative impact of the crises on number of bilateral investment agreements and their diversification –

while the positive trend persist, countries enter twice less of these agreements than it was the case before the crisis.

The rest of this paper is organized as follows: Section 2.2 provides the description of data used for the empirical exercise; Section 2.3 describes the empirical methodology, while Section A.3.3 provides the results and discuss the mechanisms of found effects. Section 1.5 provides concluding remarks.

1.2 Data

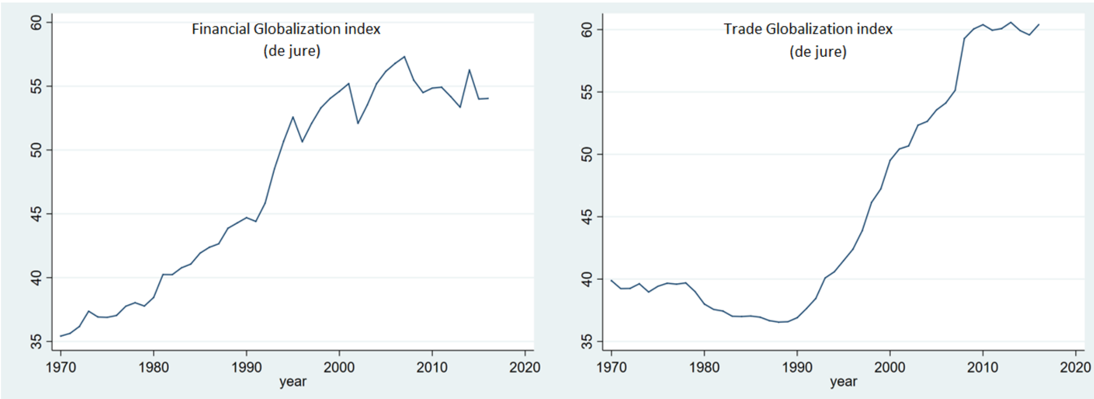
1.2.1 The KOF Globalization Index

Rather than actual international flows that react to economic crises in almost real time, we are interested in the policies that enable, facilitate and foster such flows and activities and their response to crises over a longer period of time. To measure changes in these policies we use the de jure elements contained in the KOF Globalization Index (KOFGI). The KOF Globalization Index measures globalization along the economic, social, and political dimension for 203 countries in the world since 1970. It has become the most widely used set of globalization indices in the literature.[2]

The KOF de jure Globalization index is composed of parts that measure de jure economic, social and political globalization. We are interested in the economic part of the index, i.e. the de jure Trade Globalization index (KOFTrGI, de jure) and the

[2]See Dreher (2006), Gygli et al. (2019) and https://www.kof.ethz.ch/globalisation for detailed information and data.

Figure 1.1: Historical evolution of the KOF de jure financial and trade globalization



Note: This graph shows the historical evolution of de jure Financial Globalization index (left) and de jure Trade globalization index (right) over the period between 1970 and 2018

de jure Financial Globalization index (KOFFiGI, de jure). De jure trade globalization captures policies that facilitate and promote trade flows between countries and is comprised of trade regulations, trade taxes, tariffs and trade agreements. On the other hand, de jure financial globalization measures international financial liberalization through capital account openness, investment restrictions and international investment agreements and measures the openness of a country to international financial flows and investments (Gygli et al., 2019). We recalculate the de jure financial globalization to include the measure of bilateral investment treaty diversity.[3]

[3]This dimension is originally contained in the de jure political globalization subindex as a measure of diversification of treaty partners to account for network effect of political globalization. However, after detailed inspection we found that this dimension captures bilateral investment treaties in absence of data on bilateral political treaties, as authors believe that negotiating a bilateral character is crucial for this dimension as it indicates that each party was actively involved, which is not necessarily the case for international treaties. For the purpose of our analysis, the existing formulation of political and financial subcomponents misleadingly overstates the impact of currency crises on political de jure globalization, therefore we requalify this subdimension to pertain to the financial subindex.

Figure A.2.1 shows the evolution of the KOF de jure Financial Globalization index and the KOF de jure Trade Globalization index. There is an upward trend in globalization since the 1970s, especially picking up in the early 90s. During the last decade, following the Global Financial Crisis, this steep upward trend has flattened out, highlighting the potential interaction between financial crises and globalization. While this is less obvious for the trade sub-dimension, the Financial Globalization index shows clear signs of trend breaks in 1996, 2002, 2009 and 2013. These periods coincide with one of big regional or global financial crises: the Mexican (Tequila) crisis, the Asian financial crisis, the Global financial crisis and the European Sovereign Debt crisis, providing initial evidence that financial crises do interact with globalization, in particular through financial globalization.

Table A.2.1 presents the descriptive statistics for the KOF de jure Globalization index, its sub-indices and their components used in the second part of the analysis. To make sure that we are not only measuring short-term volatility, we aggregate the data into 5-year averages prior to the analysis. This should also reduce the potential random measurement error in these indices. It is worth noting that the average period-to-period change of the KOF de jure Globalization index per country is 3.78, while for financial and trade sub-index it is 5.40 and 2.24 respectively, to provide context for interpreting the results of the analysis.

The variables that we use for the granular analysis are the subdimensions of the KOF de jure Financial Globalization index: capital account openness, investment restrictions and international investment agreements. Capital account openess is based on Chinn-Ito index measuring a country's degree of capital account openness.[4] The variable that measures investment restrictions is based on the WEF Global Competitiveness Report. The international investment agreements component covers bilateral investment agreements and treaties with investment provisions. We linearly combine it with bilateral treaty diversity to obtain the final international investment agreement measure for the analysis.

1.2.2 Currency Crises

Data on currency crises come from Systemic Banking Crises Database (Laeven and Valencia, 2018), which provides country-year-level information on episodes of financial distress. It covers 175 countries, reporting 236 currency crises around the globe during the period between 1970 and 2017. We use the currency crisis dummy variable for our analysis.

The database identifies currency crisis as a "sharp" nominal depreciation of the currency vis-à-vis the U.S. dollar. There are two thresholds for a depreciation to meet this definition: i) a year-on-year depreciation of at least 30 percent; and ii) at least 10 percentage points higher than the rate of depreciation observed in the year before. Under this definition, 236 currency crises are identified during the period 1970-2017.

We control for the size of the economy and economic growth by including the GDP per capita and real GDP annual growth variables, drawn from the World

[4]The index was initially introduced in Chinn and Ito (2006). KAOPEN is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Bank Open Source database. Real GDP per capita is given in constant prices in U.S. dollars with a base year of 2005. Furthermore, we control for different exchange rate regimes by including dummies for each of the 6 different exchange rate regimes as classified by Ilzetzki et al. (2017).

1.3 Empirical Design

Based on panel of 175 countries for the period 1975 to 2017, we estimate the impact of currency crises on the KOF de jure Globalization index and it's economic subcomponents: de jure financial globalization and de jure trade globalization. This paper tests several hypothesis: H1: Currency crises lead to policy makers' permanent sentiment shift away from globalization, leading to a prolonged deceleration in the de jure globalization. This is reflected in H2: Countries maintaining barriers to financial integration in the five-year period after the currency crisis; and H3: Countries maintaining barriers to international trade in same period; and finally: H4: Countries enter less trade and investment agreements to preserve space for the future use of protectionist policies.

To test the main hypothesis, the empirical model estimates the following equation:

$$g_{i,t} = \beta_1 g_{i,t-1} + \beta_2 crisis_{i,t-1} + \beta_3 X_{i,t-1} + \alpha_i + \gamma_t + \varepsilon_{i,t} \tag{1.1}$$

Where $g_{i,t}$ is a country-time specific measure of de jure Globalization, $crisis_{i,t-1}$ is the lagged dummy variable that takes value 1 if a country is experiencing a currency crisis in period t-1, $X_{i,t-1}$ represents a vector of lagged control variables: GDP per capita growth and log of GDP real growth to control for countries' economic development. To control for differences in exchange rate regimes we also include dummies for different exchange rate regimes (Ilzetzki et al., 2017). α_i captures a country specific effect while γ_t is a period specific effect.

To test the hypotheses 2 and 3, we use the same model structure and replace the dependent variable with de jure financial globalization and de jure trade globalization. In order to test the fourth hypothesis, we estimate the same model on the subcomponents of de jure financial globalization and de jure trade globalization related to the number of bilateral trade/financial agreements.

Globalisation processes have overall turned out to be steady and ongoing, which is why our empirical model includes the lag of its value as an explanatory variable resulting in a dynamic specification of the model. A serious difficulty arises when using fixed effects model in the context of a dynamic panel data model, particularly when the number of periods is small, as the lagged dependent variable correlates positively with the error term. Due to this correlation, any estimation using least squares procedures will produce inconsistent estimates of the relevant coefficients (Bond, 2002). To address this challenge, we employ two different approaches. First, we deduct the part of the dependent variable that is assumed to be its autoregressive part, then we regress the covariates on the remaining part of the dependent variable. We choose a range of potential levels of dependency between the dependent variable and its lag (Rho) based on the coefficients obtained by a fixed effect regression.

Alternatively, we employ one of the preferred methods in literature in dealing with dynamic models: system Generalized Method of Moments (GMM). The GMM solution to this problem involves taking first differences of the original model and using them as instruments. The first difference transformation removes both the constant term and the individual effect. Assuming the residuals of the level equation are serially uncorrelated, the values of the lagged dependent variable two periods or more serve as instruments in the first-differenced equation. The first difference estimator, however, has a caveat of its own: the instruments available for first-differenced equations are weak when the explanatory variables are persistent over time. Such weak instruments can bias the coefficients when the sample size is small. Blundell and Bond (1998) proposed a new estimator that has superior finite sample properties: system Generalized Method of Moments (GMM). System GMM is a preferred approach since it has better finite sample properties when the instruments are weak. This new estimator combines the regression in differences with the regression in levels in a system of equations in obtaining coefficient estimates. Under the following additional assumption, this new estimator exhibits superior finite sample properties in an autoregressive model with panel data. In line with Roodman (2009), the lag of the dependent variable is considered a predetermined variable, i.e. independent of current disturbances, but influenced by past ones. If a variable is predetermined and not strictly exogenous, standard treatment is to use lags 1 and longer, which we apply for the autoregressive lag. The vector of control variables enters the instrument matrix as standard, strictly exogenous, instruments.

For each method employed, we calculate the long-term impact of the currency crisis on the dependent variable by dividing the obtained coefficient on currency crisis with 1 minus the value of the autoregressive lag.

1.4 Results

To test the first hypothesis that the countries shift away from globalization policies following the currency crisis, we first assess the impact of currency crisis on the overall de jure KOF Globalization index. As currency crises, also referred to balance of payment crises, relate directly to the imbalances in the external sector, we expect policy makers' sentiment towards international integration to weaken in the medium term period post-crisis. If this is true, we expect a negative sign on the coefficient of currency crisis when estimating our model.

Table 1.1 shows the result of a regression model specified in Equation 1. The first column shows the results of a dynamic model using fixed effects panel regression. As this specification yields biased estimates, in columns 2, 3 and 4 we assume different levels of dependency of the independent variable on its lag (Rho) and deduct if from the dependent variable, estimating the model on the remaining part of the index variation. Column 5 re-estimates the model using system GMM. We find negative impact of currency crisis on the overall de jure Globalization index using our fixed effect regression strategy. Same holds true for a model estimated by the system GMM estimation, although the coefficient obtained by this estimation is lower in magnitude and significance level. When it comes to the control variables, in all specifications we find a significant positive association between the KOF de jure globalization index and the real GDP growth, as well as GDP per capita – advanced and faster growing countries are associated with higher levels of globalization than those with smaller income per capita.

Table 1.1: Impact of currency crisis on the KOF de jure Globalization index

VARIABLES	(1) KOFGI, de jure	(2) Rho=.6	(3) Rho=.7	(4) Rho=.8	(5) GMM
KOFGI, de jure (t-1)	0.73***				0.87***
	(0.03)				(0.03)
Currency crisis (t-1),	-0.60***	-0.66***	-0.61***	-0.57***	-0.46*
	(0.21)	(0.21)	(0.21)	(0.21)	(0.28)
real GDP growth (t-1), 0.07**	0.07***	0.07**	0.06**	0.09**	
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
real GDP per capita (t-1),	0.76	1.60***	0.96**	0.31	1.04***
	(0.49)	(0.50)	(0.45)	(0.42)	(0.28)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.99	0.79	0.72	0.62	
Number of Countries	149	149	149	149	149
Number of periods	8	8	8	8	8
Long-run curcr	-2.22	-1.64	-2.04	-2.84	-3.60
p-value curcr	0.01	0.00	0.00	0.01	0.10
Observations	1,005	1,005	1,005	1,005	1,005

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Globalization Index for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

In the next step of our analysis, we move to analysing the sub-indices of interest. Table 1.2 provides estimates of the estimation of the Equation 1 on the KOF de jure Financial Globalization index that measures the openness of a country to international financial flows and investments. This sub-index encompasses measures of capital account openness, investment barriers and the number and diversification of international investment agreements. While we look into these factors individually, in order to test hypotheses H2 and H4, we expect an overall negative impact of currency crisis on de jure financial globalization.

We find economically and statistically significant negative relationships between currency crises and the de jure financial globalization in all of our model specifications. When looking at the results obtained by system GMM, the occurrence of currency crisis associates with a decrease of 2.08 index points in de jure financial globalization from one period to another, corresponding to a long term decrease of 4.23. Given that the period-to-period change of this sub-component is 5.40, these results suggest that currency crises lead to deceleration of financial de jure globalization, but not the complete diminishment of its positive trend. The granular analysis will provide more evidence on the individual drivers of such a deceleration.

As currency crises are often preceded by a large current account deficit, policy makers might resort to imposition of trade barriers, in an attempt to prevent future balance of payments imbalances. We test if it is the case that the countries keep these in place for a prolonged period after the crisis in an attempt to avoid similar imbalances in the future. Table 3 provides the results of the estimation of impact of currency crisis on the KOF de jure Trade Globalization. Albeit the coefficient

Table 1.2: Impact of currency crisis on de jure financial globalization

VARIABLES	(1) KOFFiGI, de jure	(2) Rho=.6	(3) Rho=.7	(4) Rho=.8	(5) GMM
KOFFiGI, de jure (t-1)	0.70***				0.51***
	(0.02)				(0.05)
Currency crisis (t-1)	-1.76***	-2.09***	-1.77***	-1.45**	-2.08**
	(0.66)	(0.65)	(0.66)	(0.68)	(0.95)
real GDP growth (t-1)	0.06	0.07	0.06	0.04	0.14
	(0.08)	(0.08)	(0.08)	(0.08)	(0.14)
real GDP per capita, log (t-1)	-0.90	0.25	-0.86	-1.97	3.00***
	(1.36)	(1.52)	(1.37)	(1.27)	(0.53)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.92	0.42	0.31	0.23	
Number of Countries	149	149	149	149	149
Number of periods	8	8	8	8	8
Long-run curcr	-5.94	-5.24	-5.91	-7.25	-4.23
p-value curcr	0.01	0.00	0.01	0.03	0.03
Observations	1,005	1,005	1,005	1,005	1,005

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Financial Globalization Index for country *c* in period *t*, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

estimate does reflect a substantial impact of currency crises on trade related legislative barriers, these estimated are by no means statistically significant. This finding provides an insight relevant to the post Global financial crisis debate on whether the financial crises, in a broad sense, represent a factor in the recent global increase of trade barriers.

Since we do not find significant impact of currency crises trade related globalization policies, we proceed our analysis assuming that the deceleration in de jure globalization comes only from factors related to financial openness of the country. By estimating the model specified in equation 1 on its subcomponents, we test the hypotheses H2 and H4 and learn more about the individual mechanism behind the observed deceleration in financial de jure globalization.

The KOF de jure financial index is composed of a measure of current account openness, number of international investment agreements, the diversification of partners in bilateral investment agreements and investment restrictions.[5] We combine the number of international investment agreements and the measure of their diversification into one variable, as they are highly correlated, and estimate the impact of currency crises on the newly generated variable.

Table 1.4 shows results of the estimation of the impact of currency crises on capital account openness. The GMM estimation shows a slight negative impact in the 5-year period after the crisis. The negative effect of 0.30 compares to the average yearly change of the capital account openness measure that equals 0.24,

[5]We provide the analysis of the currency crisis impact on the investment restrictions in the Appendix, as it is not part of our hypotheses testing.

Table 1.3: Impact of currency crisis on de jure trade globalization

VARIABLES	(1) KOFTrGI, de jure	(2) Rho=.6	(3) Rho=.7	(4) Rho=.8	(5) GMM
KOFTrGI, de jure (t-1)	0.76***				0.86***
	(0.03)				(0.04)
Currency crisis (t-1)	-0.72	-0.78	-0.74	-0.70	-0.90
	(0.53)	(0.51)	(0.52)	(0.54)	(0.68)
real GDP growth (t-1)	-0.09*	-0.11*	-0.10*	-0.09	0.06
	(0.05)	(0.06)	(0.06)	(0.05)	(0.08)
real GDP per capita, log (t-1)	1.87*	3.03**	2.32**	1.61	1.90***
	(1.09)	(1.26)	(1.15)	(1.05)	(0.50)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.96	0.36	0.31	0.25	
Number of Countries	143	144	144	144	144
Number of periods	8	8	8	8	8
Long-run curcr	-3.034	-1.955	-2.474	-3.511	-6.277
p-value curcr	0.187	0.130	0.157	0.193	0.242
Observations	977	978	978	978	978

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Financial Globalization Index for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

indicating that there is a complete muting of the previous positive trend in countries' liberalization of the capital account.

Next, we look at the impact of currency crises on the number of investment agreements and their diversification table A.2.2. International investment agreements promote the free flow of investments between countries that enter the agreements, and therefore hinder countries from exercising the protectionist policies. Therefore, to save space for future employment of financial barriers, we argue that countries

Table 1.4: Impact of currency crisis on capital account openess

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CA openness	Rho=.5	Rho=.6	Rho=.7	GMM
CA openness (t-1)	0.63***				0.57***
	(0.03)				(0.08)
Currency crisis	-0.11	-0.15**	-0.12*	-0.08	-0.30**
	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)
real GDP growth	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
log real GDP per capita	-0.02	0.04	-0.01	-0.06	0.28***
	(0.15)	(0.17)	(0.15)	(0.14)	(0.05)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.58	0.17	0.15	0.12	
Observations	945	945	945	945	945

Note: The dependent variable is number of international investment agreements for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 1.5: Impact of currency crisis on international investment agreements (iia)

VARIABLES	(1) iia	(2) Rho=.8	(3) Rho=.9	(4) Rho=.95	(5) iia
investment agreements (t-1)	0.96***				1.17***
	(0.02)				(0.02)
Currency crisis	-1.56***	-1.25***	-1.44***	-1.53***	-2.88***
	(0.38)	(0.41)	(0.39)	(0.39)	(0.85)
real GDP growth	0.01	-0.02	-0.01	0.00	0.24**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.10)
log real GDP per capita	3.11***	5.97***	4.19***	3.30***	0.73***
	(0.91)	(1.34)	(1.02)	(0.89)	(0.23)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.95	0.55	0.49	0.46	
Observations	1,020	1,020	1,020	1,020	1,020

Note: The dependent variable is number of international investment agreements for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

will enter less international investment agreements, especially in those cases in which they would have to commit to refraining from capital controls in times of financial distress. We find a significantly negative effect of currency crisis. The negative 2.88 change compares as half of the average period-to-period increase of this variable (4.62). Therefore, the post crisis changes do not entirely mute the positive trend in the number of international agreements. However, countries enter half as many agreements in the 5-year period after the currency crisis, than they would in the absence of crisis occurrence. This is an important insight for future research and policy making, as international investments represent an important source of economic growth, job creation, infrastructure, competition, international trade and innovation. International investment agreements can be an important factor for host countries to incentivize investments, both in quantity and quality, as they provide an additional layer of security to foreign investors and promote international competition.

1.5 Conclusion

In a highly globalized world, international spillovers represent an increasingly important factor in the propagation of financial crises, highlighting the question of a potential trade-off between integration and stability, and giving way to increasingly protectionist policies. In the case of currency crisis in particular, the external sector plays a crucial role in its occurrence. This potentially gives rise to negative sentiment towards globalization and propagation of protectionist policies in the post-crisis period. We look for a long-term, structural effect of currency crisis on globalization supporting policies. We find that a currency crisis has a negative impact on the KOF de jure Globalization index, suggesting a deceleration of a positive trend that the de jure globalization has exhibited over the last decades.

Assessing the mechanisms behind this decrease, we find that this deceleration is mediated primarily through a negative effect of the crisis on the jure financial globalization. In particular, there are two different channels through which the financial openness of a country decreases after the currency crisis. First, the country slows down on its capital account liberalization, indicating that some sort of capital controls and similar barriers remain in place for a prolonged period after the crisis. Second, the countries enter less international investment agreements in order to preserve space for the future use of these barriers. This is an important insight and a potential direction for further research, as foreign investments represent one of the most important drivers of growth in developing countries, and understanding this trade-off could provide insight for policy makers necessary to assess the long-term benefits and costs of their policy responses to the currency imbalances.

1.6 Appendix

Table A.2.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
KOF de jure Globalization Index	49.06	18.93	10.75	93.61	1638
De jure Financial Globalization Index	44.74	26.90	1.00	96.70	1654
De jure Trade Globalization Index	44.64	24.03	1.58	95.94	1444
Capital account openness	-0.04	1.50	-1.92	2.33	1359
International investment agreements	14.21	24.21	0.00	169.50	1773
Investment restrictions	6.68	1.52	2.07	10.00	531

Figure A.2.1: Globalization levels by countries (2018)

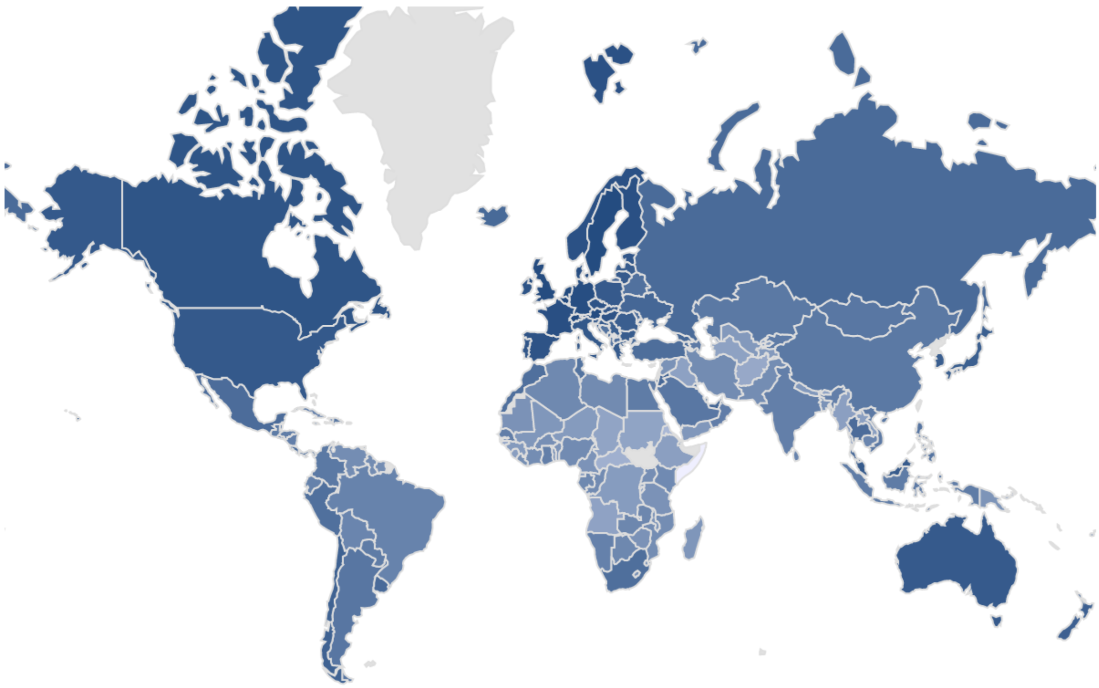


Table A.2.2: Impact of currency crisis on investment restrictions

VARIABLES	(1) yvar Restrictions	(2) yvar Rho=.2	(3) yvar Rho=.3	(4) yvar Rho=.4	(5) gmm Restrictions
Restrictions (t-1)	0.37***	0.17**	0.07	-0.03	-0.01
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Currency crisis (t-1)	-0.23*	-0.23*	-0.23*	-0.23*	-0.31
	(0.12)	(0.12)	(0.12)	(0.12)	(0.27)
real GDP growth	-0.01	-0.01	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
log real GDP per capita	1.48***	1.48***	1.48***	1.48***	0.41***
	(0.48)	(0.48)	(0.48)	(0.48)	(0.09)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.72	0.65	0.62	0.60	
Observations	354	354	354	354	354

Note: The dependent variable is number of investment restrictions for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. Real GDP growth and real GDP growth per capita are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag. Column 5 provides estimates obtained by the system GMM estimation. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.2.3: Robusstness test: Impact of currency crisis on de jure KOFGI, controlling for lagged de facto KOFGI

VARIABLES	(1) KOFGI, de jure	(2) Rho=.65	(3) Rho=.7	(4) Rho=.75	(5) GMM
KOFGI, de jure (t-1)	0.75***				0.74***
	(0.03)				(0.05)
Currency crisis (t-1),	-0.59**	-0.68***	-0.64***	-0.60**	-0.79**
	(0.24)	(0.23)	(0.23)	(0.24)	(0.33)
KOFGI, de facto (t-1),	-0.06**	-0.03	-0.05	-0.06**	0.11**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
real GDP growth (t-1),	0.07**	0.07**	0.07**	0.07**	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
real GDP per capita (t-1),	1.05*	1.60***	1.33**	1.07**	1.29***
	(0.55)	(0.57)	(0.54)	(0.52)	(0.38)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.98	0.69	0.65	0.59	
Number of Observations	1025	1025	1025	1025	1025
Number of Countries	152	152	152	152	152
Number of periods	8	8	8	8	8
Long-run effect	-2.40	-1.93	-2.12	-2.4	-2.99
p-value (lr)	0.01	0.01	0.01	0.01	0.02
Observations	1,025	1,025	1,025	1,025	1,025

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Globalization Index for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. KOF de facto globalization index, real GDP growth and real GDP growth are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag, while Column 5 presents results from a GMM model. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.2.4: Robusstness test: Impact of currency crisis on de jure KOFFiGI, controlling for lagged de facto KOFFiGI

VARIABLES	(1) KOFFiGI, de jure	(2) Rho=.65	(3) Rho=.7	(4) Rho=.75	(5) GMM
KOFFiGI, de jure (t-1)	0.64***				0.63***
	(0.03)				(0.06)
Currency crisis (t-1)	-1.24*	-1.50**	-1.35**	-1.21*	-1.82**
	(0.66)	(0.64)	(0.65)	(0.66)	(0.84)
KOFFiGI de jure (t-1),	-0.07**	-0.06*	-0.07**	-0.07**	-0.13**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
real GDP growth (t-1)	0.16*	0.16*	0.16*	0.16*	0.18*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
real GDP per capita, log (t-1)	2.25*	3.17**	2.66**	2.15*	4.13***
	(1.31)	(1.35)	(1.30)	(1.27)	(0.71)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.90	0.19	0.17	0.15	
Number of Observations	1025	1025	1025	1025	1025
Number of Countries	152	152	152	152	152
Number of periods	8	8	8	8	8
Long-run effect	-3.45	-3.32	-3.39	-3.47	-4.97
p-value (lr)	0.06	0.02	0.04	0.07	0.02
Observations	1,025	1,025	1,025	1,025	1,025

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Financial Globalization Index for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. KOF de facto financial globalization index, real GDP growth and real GDP growth are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag, while Column 5 presents results from a GMM model. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.2.5: Robusstness test: Impact of currency crisis on de jure KOFTrGI, controlling for lagged de facto KOFTrGI

VARIABLES	(1) KOFTrGI, de jure	(2) Rho=.65	(3) Rho=.7	(4) Rho=.75	(5) GMM
KOFTrGI, de jure (t-1)	0.81***				0.85***
	(0.03)				(0.03)
Currency crisis (t-1)	-0.49	-0.54	-0.49	-0.44	-0.98
	(0.59)	(0.57)	(0.58)	(0.59)	(0.64)
KOFFiGI, de facto (t-1)	-0.01	-0.01	-0.01	-0.02	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
real GDP growth (t-1)	-0.11**	-0.12**	-0.11**	-0.10*	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
log real GDP per capita (t-1)	2.36**	2.73**	2.41**	2.09*	1.77***
	(1.14)	(1.18)	(1.13)	(1.09)	(0.42)
Country FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Ex. rate regime FE	Yes	Yes	Yes	Yes	
Adjusted R-squared	0.96	0.29	0.27	0.25	
Number of Observations	1002	1003	1003	1003	1003
Number of Countries	147	148	148	148	148
Number of periods	8	8	8	8	8
Long-run curcr	-2.52	-2.16	-2.46	-2.97	-6.76
p-value curcr	0.41	0.35	0.40	0.46	0.15
Observations	1,002	1,003	1,003	1,003	1,003

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is KOF de jure Trade Globalization Index for country c in period t, and its lag is also included as a regressor in the dynamic model. Currency crisis is a dummy variable that takes value 1 if a country has experienced currency crisis in the observed period and 0 otherwise. KOF de facto trade globalization index, real GDP growth and real GDP growth are control variables that vary per country and time period. The regressions are at 5-year average frequency. Column 1 present results from fixed effects dynamic panel model estimations, columns 2, 3 and 4 re-estimates the equation assuming different dependency levels of the autoregressive lag, while Column 5 presents results from a GMM model. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.2.6: The structure of the KOF Globalization index

Globalisation Index, de facto	Weights	Globalisation Index, de jure	Weights
Economic Globalisation, de facto	*33.3*	*Economic Globalisation, de jure*	*33.3*
Trade Globalisation, de facto	*50.0*	*Trade Globalisation, de jure*	*50.0*
Trade in goods	38.8	Trade regulations	26.8
Trade in services	44.7	Trade taxes	24.4
Trade partner diversity	16.5	Tariffs	25.6
		Trade agreements	23.2
Financial Globalisation, de facto	*50.0*	*Financial Globalisation, de jure*	*50.0*
Foreign direct investment	26.7	Investment restrictions	33.3
Portfolio investment	16.5	Capital account openness	38.5
International debt	27.6	International Investment Agreements	28.2
International reserves	2.1		
International income payments	27.1		
Social Globalisation, de facto	*33.3*	*Social Globalisation, de jure*	*33.3*
Interpersonal Globalisation, de facto	*33.3*	*Interpersonal Globalisation, de jure*	*33.3*
International voice traffic	20.8	Telephone subscriptions	39.9
Transfers	21.9	Freedom to visit	32.7
International tourism	21.0	International airports	27.4
International students	19.1		
Migration	17.2		
Informational Globalisation, de facto	*33.3*	*Informational Globalisation, de jure*	*33.3*
Used internet bandwidth	37.2	Television access	36.8
International patents	28.3	Internet access	42.6
High technology exports	34.5	Press freedom	20.6
Cultural Globalisation, de facto	*33.3*	*Cultural Globalisation, de jure*	*33.3*
Trade in cultural goods	28.1	Gender parity	24.7
Trade in personal services	24.6	Human capital	41.4
International trademarks	9.7	Civil liberties	33.9
McDonald's restaurant	21.6		
IKEA stores	16.0		
Political Globalisation, de facto	*33.3*	*Political Globalisation, de jure*	*33.3*
Embassies	36.5	International organisations	36.2
UN peace keeping missions	25.7	International treaties	33.4
International NGOs	37.8	Treaty partner diversity	30.4

Weights in percent for the year 2016. Weights for the individual variables are time variant. Overall indices for each aggregation level are calculated by the average of the respective de facto and de jure indices

Chapter 2

The Role of Bank Industry Specialization in Transmission of Funding Shocks[1]

2.1 Introduction

The recent financial crisis led to a substantial rebalancing of banks' international loan portfolios. Some banks cut lending to crisis countries and moved their funds back home, others shifted their loan portfolio towards other countries.[2] While many researchers have analyzed the role that geographical specialization plays for credit reallocation after a funding shock during a banking crisis, very few have focused on

[1] This chapter is based on Boskovic et al. (2019)

[2] See Giannetti and Laeven (2012); Cetorelli and Goldberg (2011); Giroud and Mueller (2015); Popov and Van Horen (2015) for evidence of domestic and international loan portfolio relocation of banks.

the impact of other types of bank portfolio concentration, such as concentration by industry.[3]

Banks specialize in certain industries to acquire an informational advantage. Soft information about borrowers in their main industries allows them to better gauge the quality of a firm during times of general economic distress. When engaging in relationship lending, banks gather propriety information about their customers through repeated interactions (Boot, 2000). Banks will typically have gathered more sector-specific knowledge in sectors where they are specialized, improving their screening abilities and reducing the need for costly monitoring in these sectors. As such, while banks that face a funding shock during a banking crisis are forced to reduce lending, they have an incentive to shield sectors in which they are specialized and have relatively superior screening and monitoring skills (De Jonghe et al., 2020). The more the bank focuses on certain industries, the more it can acquire industry-specific knowledge and thereby realize specialization benefits, i.e., reduce, on average, the credit risk of the loan portfolio. However, a concentrated loan portfolio leads to increased concentration risks due to higher default correlations of borrowers within a given industry (Jahn et al., 2016). Despite proven advantages and disadvantages of portfolio specialization in good times, it remains an open question whether ex-ante specialization of banks in certain industries will lead to differential reallocation effects in bank portfolios across industries during a funding shock.

[3] See Beck et al. (2021); Degryse and Ongena (2007); Jahn et al. (2016); Giannetti and Saidi (2019); for evidence and implications of bank portfolio concentration.

We look at how banks' industry specialization affects lending during a banking crisis in the borrower country. For the analysis we use data on worldwide syndicated loans from Thomson Reuters Dealscan. By comparing the lending behavior of specialized banks to unspecialized banks to the same borrower, we address the concern that differences in loan demand biases the results on bank lending. Our regressions therefore estimate the marginal propensity of a bank to lend to firms in specialized industries rather than firms in non-specialized industries during a crisis. Additionally, we employ a combination of bank-firm, bank-time and firm-time fixed effects to address a number of alternative explanations.

We find that banks mitigate the transmission of the banking crisis by mantainining higher loan growth to firms in their specialized industries by 3.90%. By combining the benefits of firm specific soft information and sectoral knowledge, banks are able to better discern the healthy borrowers in times of market-wide stress. This impact becomes signficant for lending to all firms in a specialized industry after a lag of 6 months, when banks shield entire sectors to preserve the industry specific knowledge at large. In this case, banks with a one standard deviation higher industry specialization mantain the loan volume to all firms in these industries that is higher by 10.08% than the average firm, two quarters after the banking crises.

Next, we estimate how these effects spill over to connected countries with no crisis through cross-border bank lending, and the differential transmission to specialized industries. To illustrate this spillover effect, suppose a bank operates in both Poland and Spain while only Poland is experiencing a banking crisis. In order to offset the capital shock in Poland, the bank may reduce lending to Spain in order to re-channel the funds to borrowers in Poland through the banks' internal capital market, which gives rise to contagion. Giannetti and Saidi (2019) show that there is the home bias in the international allocation of syndicated loans increases in the presence of adverse economic shocks, with two possible reasons: First, the cost of negotiating and monitoring syndicated loans may be higher for foreign loans. Second, in response to negative shocks, banks face increased uncertainty regarding their ability to meet their capital requirements and, as a result, their effective risk aversion increases. As the flight home effect relates to the ability to monitor the quality of borrowers abroad, we expect that there will be an adverse spillover effect on non-specialized industries in connected countries, while this negative effect will possibly be mitigated by the banks' specialization in firm's industry. We find that banking crises do spill over to other non-crisis countries through cross-border lending: Banks operating in a country that experiences a banking crisis reduce loan supply in non-crisis countries by 42%, when controlling for firm demand. Moreover, this spillover effect is strongest to those industries in which the bank is not specialized in. On the other hand, banks that have one standard deviation higher industry specialization entirely mute the negative spillover effect to those industries. Therefore, the industries with lower presence of specialized banks are more prone to cross-border banking crisis contagion.

While the banks shield their specialized industries in countries with crisis by mantaining higher loan volume to their relationship firms from those industries, improving the monitoring skills and ability to discern the healthy borrowers in times of demand shock, in countries with no crisis they are more concerned with perserving the sector wide knowledge, shielding entire sectors and mantaining higher loan growth to whole industries.

Our paper contributes to the existing literature in several ways. First, it relates to the literature that explores the effects of banks' loan concentration on liquidity provision (Giannetti and Saidi, 2019). In their paper, De Jonghe et al. (2020) use Belgium credit register data and show that sector specialization, together with sector presence and firm risk has an important role in banks' lending decisions. In contrast, we use a detailed cross-country dataset which allows for an assessment of international spillover effects. Moreover, Paravisini et al. (2014) document the importance of bank specialization on lending decisions, but focusing on the real effects on exporting firms.

Second, our results contribute to the growing literature on bank funding shock transmission and cross-border spillovers. Several authors have documented a negative effect of funding shocks on lending (Puri et al., 2011; Cetorelli and Goldberg, 2011). The importance of geographical specialization has also been adressed in several papers: Giannetti and Laeven (2012) show that the collapse of international markets during financial crises can in part be explained by a flight home effect, while De Haas and Van Horen (2013) show that geographical proximity of banks' connected markets plays a role in banks' portfolio reallocation.

The policy implications of our findings refer to a potential positive impact of bank lending concentration in times of banking crisis, that is usually considered to be negative, as it implies potential concentration of risk. On the other hand, the firms borrowing from banks with lower specialization in their industry may be more vulnerable and have more difficulties in accessing financing in times of market wide distress.

The rest of the paper is organized as follows. First we provide the description of the data and the construction of variables in Section 2.2. In Section 2.3, we discuss the empirical methodology that is used to address the research question, focusing on identification challenges. Section A.3.3 presents the results of our main analysis in two sections: The role of industry specialization in allocation of credit in the country experiencing banking crisis (Section 2.4.1) and the international spillover effects to the non-crisis countries (Section 2.4.2).

2.2 Data

For our main analysis and the construction of bank industry specialization, we use data on worldwide syndicated lending from Thomson Reuters Dealscan. Syndicated lending constitutes a significant share of total lending. Around one-third of total international lending is done through the syndicated loan market and it is an important source of financing in both developed and emerging economies (Cerutti et al., 2017). Syndicated loans are issued jointly by a group of banks to a single borrower. The lending syndicate includes at least one lead bank (also called lead arranger) and usually further participant banks. Lead banks negotiate terms and conditions of deals, perform due diligence, and organize participants. Therefore, lead arrangers stand in direct contact with the borrower and retain larger loan shares for signaling purposes. Participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers.

Dealscan provides extensive information on syndicated loans at origination, including loan amount, maturity, and interest, as well as identity of lenders and borrowers. We restrict our analysis to loans by banks to non-financial firms and consider lending only by commercial, savings, cooperative and investment banks.[4] All data are aggregated at banks' and firms' parent company, consistent with the literature. We keep only lead arrangers and drop participants from our sample as we are interested in loan supply conditional on bank expertise in the specific industry. The dataset provides the identification of the lead arranger in each loan. Since participants are usually not in direct contact with the borrower and do not screen the borrower either, they are not able to collect soft information on the specific industry upon supplying credit.

Our full sample covers the years 1995 to 2010 and is composed of two separate levels of aggregation. First, we aggregate this data to form 487,098 observations at the bank-industry-quarter level. Next, to be able to capture differences in firms' demand, we construct the data on a more granular level, the bank-firm-quarter (loan) level. The dataset contains information on 32,290 firms and 358 banks from 42 countries accross the world, forming a total of 899,098 observations. An average bank in the sample lends to 34.7 firms, or 12.6 industries. Tables A.2.1 and A.2.2 provide detailed summary statistics of the main variables for both levels of data aggregation.

[4]In Dealscan, we include only the lender types Commercial Banks, Finance Companies, Investment Banks, Mortgage Banks, Thrift/S&L, and Trust Companies. Investment banks constitute 3% of our sample and excluding them does not change results. Borrower types included are Corporations, Insurance Companies, Law Firms, Leasing Companies and Other. See Doerr and Schaz (2017) and Schaz (2019) for further details on data construction using Dealscan data.

Table A.2.1: Summary statistics (*bank-firm-level sample*)

VARIABLES	mean	sd	min	max	N
Industry specialization $\in [0,1]$	0.03	0.09	0.00	1.00	899,098
Loan volume (\$m)	200.63	531.70	0.01	46,100	899,098
Loan growth %	4.02	1.96	-3.08	7.94	899,098
Banking crisis $\in \{0,1\}$	0.26	0.44	0.00	1.00	899,098
Connected countries $\in \{0,1\}$	0.38	0.48	0.00	1.00	899,098

Note: This table shows summary statistics of variables at the bank-firm-quarter level. *Industry specialization* is the relative importance of an industry for a bank (across all countries), defined as the ratio of all credit granted by bank b to industry i in quarter q relative to bank b's total credit granted in the same period. *Loan volume* (in millions of USD) is the outstanding loan volume by bank b to firm f in quarter q. *Loan growth* is the quarterly growth of *Loan volume*. *Banking crisis (BC)* is a dummy variable with value one during banking crises in the firm country. *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t.

Table A.2.2: Summary statistics (*bank-industry-level sample*)

VARIABLES	mean	sd	min	max	N
Industry specialization $\in [0,1]$	0.04	0.11	0.00	1.00	487,098
Loan volume (\$m)	266.98	490.18	0.07	5,810	487,098
Loan growth %	4.36	1.86	-2.70	8.67	487,098
Banking crisis $\in \{0,1\}$	0.25	0.43	0.00	1.00	487,098
Connected countries $\in \{0,1\}$	0.33	0.47	0.00	1.00	487,098

Note: This table shows summary statistics of variables at the bank-industry-country-quarter level. *Industry specialization* is the relative importance of an industry for a bank (across all countries), defined as the ratio of all credit granted by bank b to industry i in quarter q relative to bank b's total credit granted in the same period. *Loan volume* (in millions of USD) is the outstanding loan volume by bank b to all borrowers of industry i in quarter q. *Loan growth* is the quarterly growth of *Loan volume*. *Banking crisis (BC)* is a dummy variable with value one during banking crises in the borrower country. *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t.

To measure industry specialization of a bank, we construct a variable based on the relative importance of an industry for a bank by lending volume across all countries. We define industry specialization as the ratio of all loans granted by bank b to all borrowers from industry i relative to bank b's total loans granted in quarter t:

$$Industry\ specialization_{b,i,t} = \frac{\sum_{f=1}^{F} loans_{b,f,i,t}}{\sum_{i=1}^{I} \sum_{f=1}^{F} loans_{b,f,i,t}}, \tag{2.1}$$

where F captures the total number of firms with outstanding loan volume from bank b that belong to industry i at time t. Similarly, I is the total number of industries i to which bank b has outstanding loan volume in quarter t. $Loans_{b,f,i,t}$ measures the total outstanding lending volume (in millions of USD) from bank b to borrowing firm f from industry i in quarter t. $Industry\ specialization_{b,i,t}$ takes values between 0 and 1, where 0 means absence of lending to industry i, while 1 indicates that all recorded lending by a specific bank goes to industry i in quarter t. We use this variable both for analysis at the bank-firm-quarter and at the bank-industry quarter level. Figure A.3.2 plots the left-skewed distribution of banks' *industry specialization* around the mean value of 0.03 at the bank-firm-quarter level; this distribution shows that banks are highly diversified across industries.

Data on banking crises are drawn from Laeven and Valencia (2013)'s Systemic Banking Crises Database, which provides country-year-level information on episodes of financial distress.[5] From 1995 to 2010, it reports 148 banking crisis (BC) observations at the country-year level. As banking crises in the dataset last for one to five years, we assign the banking crisis shock to each quarter in each year that is identified as the crisis year. The two conditions that define a banking crisis are i) significant signs of financial distress in the banking system (such as bank runs, losses in the banking system, and/or bank liquidations); and ii) significant banking policy intervention measures in response to the losses in the banking system. Figure A.3.1 plots the number of years with a banking crisis for each country. In our sample, there is a concentration of financial turmoil around the time of the Asian crisis in 1997 and from 2008 onward, during the Great Financial Crisis.

2.3 Empirical Methodology

We examine how banks' industry specialization affects lending during banking crises at two levels of aggregation. First, we analyze bank lending behavior to specialized industries on aggregate at bank-industry-quarter level. Second, we isolate loan supply from loan demand on the granular firm-bank-quarter level (loan level) to establish lending to firms. Finally, we analyze whether banking crises spill over to other non-crisis countries through cross-border lending and whether this contagion depends on banks' industry specialization.

[5]Laeven and Valencia (2013) is the most comprehensive database on financial crises occuring after 1970.

2.3.1 Lending to Industries

To analyze whether banks protect their specialized industries on aggregate, we start with the coarser bank-industry-quarter level data, estimating the regression equation 2.2.

$$
\begin{aligned}
Log(loan)_{b,i,c,t} = & \gamma_1 BC_{c,t} + \gamma_2 SPEC_{b,i,t-1} + \gamma_3 SPEC_{b,i,t-1} \times BC_{c,t} \\
& + \psi_{b,t} + \tau_{c,i,t} + \theta_{b,c,i} + \varepsilon_{b,i,c,t}
\end{aligned}
\tag{2.2}
$$

The dependent variable $Log(loan)_{b,i,t}$ denotes the logarithm of outstanding syndicated loan volume of *all* firms in industry i borrowing from bank b in period t. The banking crisis dummy $BC_{c,t}$ takes value 1 during a crisis in country c in quarter t, and 0 otherwise; $SPEC_{b,i,t-1}$ denotes bank b's industry specialization in industry i in time period $t-1$ as defined in Equation (2.1). In order to avoid contemporaneous effects of industry specialization on loan growth, we lag specialization by one period. To assess the effect of specialization on loan supply during banking crises in the borrower country, we interact industry specialization with a banking crisis dummy. We cluster standard errors on the bank level to account for correlation of loans issued by the the same bank across industries.

We estimate variants of regression Equation (2.2) employing different combinations of fixed effects. $\psi_{b,t}$ are bank-time fixed effects and capture all time-varying unobserved heterogeneity across banks. For instance, $\psi_{b,t}$ control for idiosyncratic shocks to banks' total credit supply and other changes at the bank-time level. The key identification challenge is to absorb loan demand in order to interpret results as an effect of financial shock on loan supply. The concern is that changes in firm's demand for loans over time may bias the results on bank lending. It may well be that banks specialize in certain industries because firms in this industry are more profitable or crisis resilient. Thus, loan demand by firms in specialized industries may be higher during banking crises, which affects banks lending decision. While the firm-level analysis allows for full control over the loan demand, by introducing firm fixed effects, we adress the issue at this level of aggregation by assuming the homeogneity of firm demand accross industry i i country c and by including country-industry-time fixed effects $\tau_{c,i,t}$. $\theta_{b,c,i}$ denote bank-country-industry fixed effects to absorb time-invariant characteristics at the bank-industry-country level, capturing an existing relationship of a bank with a given industry in a given country. The main coefficient of interest, γ_3, captures the differential propensity of bank b to lend to borrowers in their specialized industry i rather than to borrowers from non-specialized industries during a crisis.

2.3.2 Lending to Firms

After analyzing the effect of industry specialization on bank lending to industries overall, we move to the more granular, loan level, which allows us to identify and isolate firm specifics. Our baseline specification tests how bank industry specialization affects their loan volume to firms in normal times and in times of crises:

$$\begin{aligned} Log(loan)_{b,f,t} = &\beta_1 BC_{c,t} + \beta_2 SPEC_{b,i,t-1} + \beta_3 SPEC_{b,i,t-1} \times BC_{c,t} \\ &+ \theta_{b,t} + \tau_{f,t} + \phi_{b,f} + \varepsilon_{b,f,t} \end{aligned} \tag{2.3}$$

The dependent variable $Log(loan)_{b,f,t}$ is the logarithm of total outstanding loan volume by bank b to firm f in quarter t; *banking crisis (BC)* is a dummy with value 1 during banking crises in the firm country c in quarter t, and 0 otherwise. $SPEC_{b,i,t-1}$ is bank industry specialization, lagged by one period. $\theta_{b,t}$ denote bank-time fixed effects, $\tau_{f,t}$ firm-time fixed effects and $\phi_{b,f}$ denote bank-firm fixed effects. We cluster standard errors at the bank level. The identifying assumption is that banking crises at the aggregate country level are exogenous to the granular bank-firm lending decision. Banking crises are times of aggregate scarce capital and thus β_3 captures how this funding shock is transmitted to firms depending on banks' industry specialization.

In order to adress the main identification challenge, the granularity of our data allows us to fully absorb firm loan demand. Following the literature to separate out loan supply from loan demand, we estimate our model on the most granular firm-bank-quarter level where we employ firm-time fixed effects (Khwaja and Mian, 2008; Jiminez, Mian, Peydro, and Saurina Salas, 2010; Jiménez, Ongena, Peydró, and Saurina, 2014; Morais, Peydro, and Ruiz Ortega, 2019). Firm-time fixed effects allow shocks to affect each firm differentially at each point in time. Doing so, we control for unobservable time-varying firm characteristics (for example firm profit, risk and managerial quality) to identify loan supply. Essentially, we measure the marginal propensity of bank b to lend to firm f that is part of their specialized industry i rather than to other firms from non-specialized industries during a crisis. After absorbing any changes in loan demand our estimates reflect loan supply effects. Bank-time fixed effects capture all time-varying unobserved heterogeneity at the bank level, controlling for idiosyncratic shocks to banks' total credit supply and other changes at the bank-time level. Finally, firm-bank fixed effects use the variation within the same firm-bank relationship over time and thereby control for unobservable and time-invariant bank and firm heterogeneity (such as location or legal form); firm-bank fixed effects also control for unobservable time-invariant characteristics at the bank-firm level, such as distance and relationship.

2.3.3 Spillover Effects

We now turn to the question how banking crises spill over to other countries through cross-border bank lending and whether industry specialization mutes or amplifies this effect. We define a spillover effect of a banking crisis country to a third country through the reduction in lending of a bank that operates in both countries. Suppose a bank operates both in Poland and Spain and only Poland experiences a banking crisis. To offset the shock to capital in Poland, the bank may reduce lending to borrowers in Spain in order to rechannel funds towards Poland, through the banks' internal capital market, in order to maintain lending. Therefore, banking crises may spill over to countries that are themselves unaffected by a banking crisis via a connection to a banking crisis country through a bank that operates in both markets.

To measure spillover effects we introduce the dummy variable $CON_{b,c',t}$, which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t, if at least one other country c, to which bank b is actively lending, experiences a banking crisis in t. In the spirit of Giroud and Mueller (2015) the coefficient on CON shows how lending changes to all *connected countries* c' that borrow from bank b, but do not experience a crisis themselves. To test for spillover effects we run variants of the following regression equation:

$$Log(loan)_{b,i,c,t} = \rho_1 BC_{c,t} + \rho_2 SPEC_{b,i,t-1} + \rho_3 SPEC_{b,i,t-1} \times BC_{c,t} + \rho_4\ CON_{b,c',t} \\ + \rho_5\ CON_{b,c',t} \times SPEC_{b,i,t-1} \psi_{b,t} + \tau_{c,i,t} + \theta_{b,c,i} + \varepsilon_{b,i,c,t} \tag{2.4}$$

The equation 2.4 builds up on the equation 2.2 and introduces the variables capturing the spillover effects. The dummy variable $CON_{b,c',t}$, which equals one for all non-crisis countries $c' \neq c$ in which bank b is actively lending to and that do not experience a contemporaneous banking crisis ($BC_{c',t} \neq 1$), if at least one other active lending country c of bank b experiences a banking crisis at time t ($BC_{c,t} = 1$). To analyze the differential impact of bank specialization on crisis spillover effects, we interact *connected* with bank's industry *specialization*. The coefficient of interest, ρ_5, measures the differential transmission of lending cuts to specialized industries compared to non-specialized industries in connected countries without crisis.

Similarily, at the bank-firm-quarter level, we estimate the following model:

$$Log(loan)_{b,f,t} = \delta_1 BC_{c,t} + \delta_2\ SPEC_{b,i,t-1} + \delta_3 SPEC_{b,i,t-1} \times BC_{c,t} + \delta_4\ CON_{b,c',t} \\ + \delta_5\ CON_{b,c',t} \times SPEC_{b,i,t-1} + \phi_{b,f} + \theta_{b,t} + \tau_{f,t} + \varepsilon_{b,f,t} \tag{2.5}$$

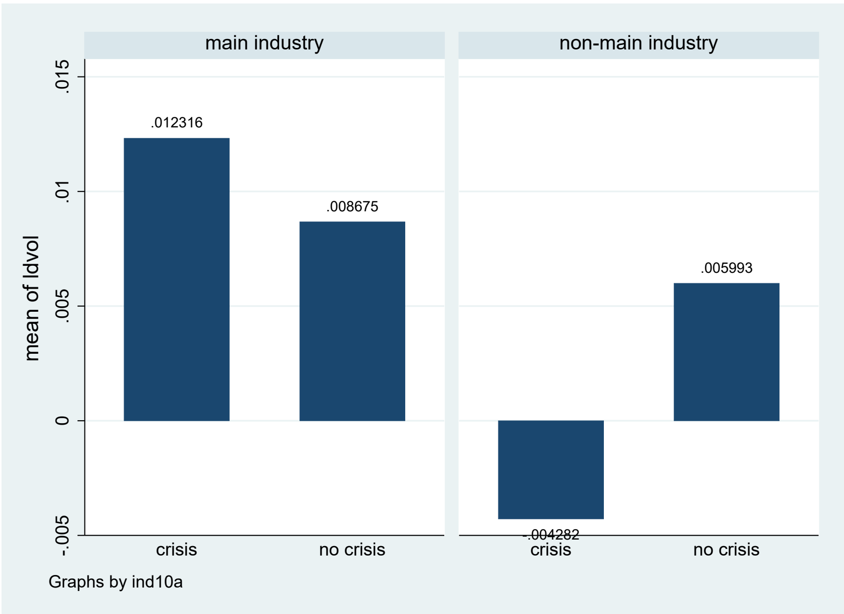
where the coefficient of interest, δ_5, measures the differential transmission of lending cuts to specialized industries compared to non-specialized industries in connected countries without crisis.

2.4 Results

2.4.1 Main Results

We present the main results in two steps. First, we analyze effects of industry specialization on banks' overall industry lending at the bank-industry-quarter level. Next, we analyze the loan supply effect of bank's industry specialization during banking crises on firms at the bank-firm-quarter (loan) level. The latter allows us to control for unobservable time-varying heterogeneities at both the bank-level and firm-level.

Figure A.2.1: Loan volume growth by main industry (10%)



Note: This figure shows the difference in loan volume extended to main versus non-main industries on bank-firm-quarter level, when there is a banking crisis versus when there is not. Main industry is defined as industry i that have more than 10% share in bank's b portfolio.

Before we move to the regression analysis, Figure A.2.1 shows the stabilizing effect of bank industry specialization on lending to their main industries during banking crises using simple sample correlations. The figure plots average loan growth during crisis and non-crisis times to all borrowers, comparing this effect to banks' main industries and to their non-main industries. We define main industries as those industries that make up for more than 10% of the lending share in a bank's loan portfolio as defined in Equation (2.1).[6] The figure suggests that banks extend more loans to their main industries both in times of crisis and no crisis. Furthermore, the right panel shows that banks reduce lending to borrowers from their non-main industries during banking crises. However, banks maintain lending to firms from their main industry that is similar during crisis and no crisis times. We now test whether this pattern holds in the regression analysis.

To analyze whether banks protect their specialized industries on aggregate we start with the coarser bank-industry-quarter level. Table A.2.3 presents results for regression Equation (2.2) examining the impact of banking crisis on specialized and non-specialized industries. The dependent variable is the logarithm of outstanding loan volume of bank b to industry i at quarter t, which is interpreted as a loan growth. For estimation, column (1) uses within-bank variation, while column (2) additionally exploits within-industry variation through bank and industry time-variant fixed effects respectively; Column (3), in addition to within bank variation, uses the variation within bank-industry-country relationship.

[6] As can be seen from Table A.2.1, the mean of banks industry specialization is 0.03% and using cut-offs between 3% and 10% share to define main idnustry yields similar graphs.

Table A.2.3: Effect of bank specialization on loan supply to industries

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)
banking crisis (BC)	0.66***		-0.05
	(0.18)		(0.05)
Industry spec. (t-1)	6.65***	5.56***	4.55***
	(0.28)	(0.23)	(0.31)
BC X Industry spec. (t-1)	-0.34	-0.05	0.57***
	(0.37)	(0.30)	(0.18)
Observations	430,460	427,875	428,617
R-squared	0.46	0.68	0.88
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Bank*Country*Industry FE	-	-	Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows regressions on the bank-country-industry-quarter level. The dependent variable is log difference of total outstanding loan volume by bank b to all borrowers in industry i in country c in quarter t; *banking crisis (BC)* is a dummy with value one during banking crises in the firm country; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). The interaction term *BCXIndustry spec.* measures the differential transmission of lending cuts to specialized industries compared to non-specialized industries during banking crisis. *** p<0.01, ** p<0.05, * p<0.1

While the first two specifications provide no statistically significant role of industry specialization in the transmission of shocks to industries, the last specification yields a significant and positive coefficient on the interaction term between banking crisis and industry specialization, signalling that that higher the specialization of a bank in an industry leads to higher loan growth to their relqationship firms from specialized industries in times of crisis. Banks with one standard deviation higher industry specialization extend loan volume to that industry that is $(0.09 \times 0.57 =)$ 5.13% higher than the average, during banking crises. Contrasting these results to Column 2, suggests that banks do not tend to inrease loan volume to industries that are globally important for the bank if they do not already have an outstanding lending relationship.

With respect to the impact of banking crisis, we find that banks actually expand their lending overall, before controlling for industry specific demand shocks. Since this effect disappears when controlling for firm demand, it is an indication that it is a demand shock that leads this potential initial increase. It is also important to note that the effect turns negative when excluding the period of the Great financial crisis (Table A.3.3) indicating that the captured effect is specifically related to this particular crisis. Indeed, the literature suggest that during this time there was a simultaneous run by borrowers who drew down their credit lines, leading to a spike in commercial and industrial loans reported on bank balance sheets (Ivashina and Scharfstein, 2010).

We move to the more granular bank-firm-quarter (loan) level to examine how individual firm demand and bank-firm relationship affect the previous findings. Table A.2.4 presents results for regression Equation (2.3) at the loan level. The model

Table A.2.4: Effect of bank specialization on loan supply to firms

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
Banking crisis (BC)	0.77**			-0.02
	(0.31)			(0.02)
Industry spec. (t-1)	6.59***	5.24***	4.99***	1.92***
	(0.43)	(0.30)	(0.38)	(0.16)
BC X Industry spec. (t-1)	-1.11**	-0.62	0.93	0.40***
	(0.52)	(0.39)	(0.64)	(0.13)
Observations	837,028	750,917	286,095	834,046
R-squared	0.50	0.66	0.80	0.95
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-	-
Firm*Time FE	-	-	Yes	-
Bank*Firm FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm-quarter (loan) level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). The interaction term *BCXIndustry spec.* measures the differential transmission of lending cuts to firms in specialized industries compared to those from non-specialized industries during banking crisis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

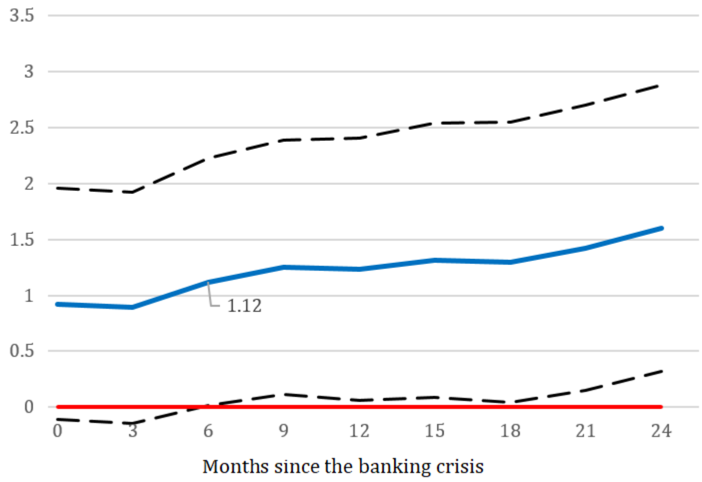
specification that does not account for firm demand show a negative relationship between bank industry specialization and loan volume in times of crisis. However, when including firm fixed effects this effect disappears, indicating that the loan demand by firms in specialized industries is on average weaker and less resilient during crises compared to firms from non-main industries.

Before moving to the coefficient of interest, i.e. the interaction term, it is worthwhile noting that banks specialization plays a role in allocation of credit in normal times. The evidence, captured by the coefficient of $Industry\ spec._{b,i,t}$ is robust across different specifications of the model and on both levels of aggregation. Banks with one standard deviation higher industry specialization mantain a loan growth to firms in specialized industries that is 44.91% higher than the average.

When it comes to the impact of interest, we find that banks' industry specialization plays a role in transmission of funding shock to the firms during the banking crisis only within existing bank-firm relationship, similarly to what we find on the industry level. Increasing lending to relationship firms from specialized industries suggests that banks are at this point more concerned with increasing their ability to estimate borrower's repayment capacities, than with sectoral spillover effects. Combining soft information on borrowers collected through long standing relationship with banks' industry specific knowledge obtained through a certain degree of specialization leads to improvement of banks' monitoring abilities in order to discern and protect heathy borrowers in times of marked-wide stress accompanied by a demand shock.

To address the possibility that banks try to preserve the industry informational advantage for whole sectors, at a later stage, following De Jonghe et al. (2020), we examine whether the coefficient of the interaction term as specified in Column 2 of A.2.4, measuring the loan growth to specialized industries to all firms in a specialized industry, turns significant when using different lag structures. We reestimate the model using bank-time and firm-time fixed effects on loan volume using different time-horizons following a banking crisis (Figure A.2.2). While the effect is statistically insignificant in first two quarters, it turns significant and positive with an upward trend in the period of 6 to at least 24 months following the banking crisis. After 6 months from the onset of the banking crisis, banks with a one standard deviation larger level of industry specialization have a lending volume that is (0.09×1.12

Figure A.2.2: Timing of the effect of industry specialization



Note: This figure illustrates the timing and magnitude of the reallocation of credit across industries following a banking crisis. The panels contain information on the interaction effect of the banking crisis and bank industry specialization. We plot the coefficients and 90% confidence bounds (dashed lines) for the interaction coefficients obtained from 9 separate estimations.

=) 10.08% higher than average. This indicates that protecting the industry specific knowledge as a whole comes into play at a later stage, when the acute part of the crisis is overcome.

To summarize the main results, while we provide statistically significant evidence that banks favor industries which are dominant in their lending portfolio in good times, the evidence that they protect these industries overall during a banking crisis is mixed. At the onset of the crisis, the industry specialization matters only within bank-firm relationship, indicating that banks maintain higher loan growth to the relationship firms from their specialized industries, arguably due to additional improvement of monitoring skills for these firms resulting from combined benefits of soft information on borrowers and their industries. However, banks protect their industry specific knowledge more broadly at a later stage, when banks provide higher loan growth to specialized industries at the exstensive margin as well. The industry information becomes relevant for loan growth to all firms within specialized industries 6 months after the shock and remains important for at least 24 months.

2.4.2 Spillover Effects

We now turn to the question how banking crises spillover to other non-crisis countries through cross-border lending and the differential impact of industry specialization on this spillover effect. We examine whether banking crises spill over to the same industries elsewhere and whether banks infect industries in which they have specialized differently.

Table A.2.5 reports results of estimating the regression at the bank-industry-quarter level. We find evidence for contagion effects as banks reduce lending to industries that are in *connected* non-crisis countries. Column (1) indicates that banks reduce loan growth to all industries that are in a borrower country that experiences a banking crisis by 71%, which corresponds to the initial increase of lending in countries with active crisis, as documented in Tables A.2.3 and A.2.4. This finding suggests that there is indeed a re-channeling of funds from connected countries to crisis countries – banking crises do spill-over to industries in non-crisis countries through banks operating in both countries. When controlling for industry-country-time specific demand, this effect is reduced by half, equaling a 43% decrease.

During a banking crisis in a connected countries, banks mantain higher growth of loans in countries with no crises to those industries in which they are specialized in, as indicated by the positive interaction term ($connected \times SPEC$). For connected

Table A.2.5: Spillover effect of bank specialization on loan supply to industries

	(1)	(2)	(3)
VARIABLES	log(loan)	log(loan)	log(loan)
Banking crisis (BC)	0.09*		-0.05*
	(0.05)		(0.03)
Industry spec. (t-1)	5.83***	5.00***	4.35***
	(0.22)	(0.20)	(0.29)
BC X Industry spec. (t-1)	1.01***	0.90***	0.93***
	(0.37)	(0.33)	(0.19)
connected	-0.71***	-0.43***	-0.03
	(0.16)	(0.14)	(0.03)
Connected X Ind. spec. (t-1)	5.98***	4.83***	1.67***
	(0.92)	(0.63)	(0.32)
Observations	430,460	427,875	428,617
R-squared	0.47	0.68	0.88
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Bank*Country*Industry FE	-		Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-country-industry-quarter level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in country c in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. The interaction term *ConnectedXIndustry spec.* measures the differential transmission of lending cuts to firms in specialized industries compared to those in non-specialized industries in connected countries without crisis. *** p<0.01, ** p<0.05, * p<0.1

countries prone to crisis contagion, a one standard deviation higher level of industry specialization leads to a higher loan growth to industry i by $(0.09 \times 4.83 =)$ 43.47 % (when controlling for industry specific demand shocks). This is economically significant as one standard deviation higher level of industry specialization fully undoes the spillover effect to the connected industry.[7]

Table A.2.6 shows results of estimating regression Equation (2.5) at the bank-firm-quarter level. In columns $(1) - (4)$ we employ bank-time fixed effects to absorb time-varying unobservable factors at the bank level such as the bank's total loan supply, profitability or size. In order to absorb loan demand, we first implement industry-country-time fixed effects in column 2 and then firm-time fixed effects in column 3. In column 1, we find evidence for spillover effects as banks that operate in a country that experiences a banking crisis reduce loan supply to firms in connected non-crisis countries. However, this effect disappears when controlling for firm demand in connected countries. The coefficient of interest of the interaction term ($connected \times Industry\ spec.$) is positive and statistically significant across all specifications. Results are robust to the absorption of loan demand through firm-time fixed effects as reported in column (3). One standard deviation higher level of industry specialization leads to a $(0.09 \times 2.76) = 24.84$ % higher loan volume growth to firms in specialized industries and therefore mitigates spillover effects to the connected country. Contrary to the differences in timing of the effect of industry specialization in banking crisis countries, the effect of industry specialization on

[7]While the coefficieint on the interaction term $BCXInd.\ spec$ turns significant, we bellieve this is due to a multicollinearity, since there is correlation between BC and *Connected*, BC X $Ind.\ share$ and *Connected* X $Ind.\ spec$ also correlate. However, the effect of *Connected* X $Ind.\ spec$ is robust to the exclusion of the correlated variables, as shown in tables A.3.1 and A.3.2.

Table A.2.6: Spillover effect of bank specialization on loan supply to firms

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
Banking crisis (BC)	0.16*			-0.01
	(0.09)			(0.02)
Industry spec. (t-1)	5.70***	4.84***	4.39***	1.86***
	(0.32)	(0.28)	(0.38)	(0.16)
BC X Industry spec. (t-1)	-0.01	-0.12	1.67**	0.48***
	(0.55)	(0.40)	(0.65)	(0.14)
Connected countries	-0.71***	-0.10	-0.22	0.00
	(0.24)	(0.11)	(0.15)	(0.01)
Connected X Ind. spec. (t-1)	4.21***	2.30***	2.76***	0.37**
	(0.93)	(0.70)	(0.52)	(0.15)
Observations	837,028	750,917	286,095	834,046
R-squared	0.50	0.66	0.80	0.95
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-	-
Firm*Time FE	-	-	Yes	-
Bank*Firm FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-firm-quarter (loan) level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. The interaction term *ConnectedXIndustry spec.* measures the differential transmission of lending cuts to specialized industries compared to non-specialized industries in connected countries without crisis. *** p<0.01, ** p<0.05, * p<0.1

shock transmission in connected countries is steady over time (see figure A.3.3). The banks provide 3.33% higher loan growth to the relationship firms in their specialized industries, as indicated by the results obtained in the last column, indicationg that soft information from bank-firm relationship is less important than the industry information in the case of internationa spillover effects.

To conclude, we find that banking crises spill over to other non-crisis countries through cross-border lending. We document that banks reduce lending to industries in non-crisis countries in response to a banking crisis in one of their active countries. However, banks shield the borrowers in their main industries from this spillover effect by mantaining higher credit growth to the specialized industries. This indicates that the industries with lower presence of specialized banks are more prone to banking crisis contagion operating through cross-border lending.

2.5 Conclusion

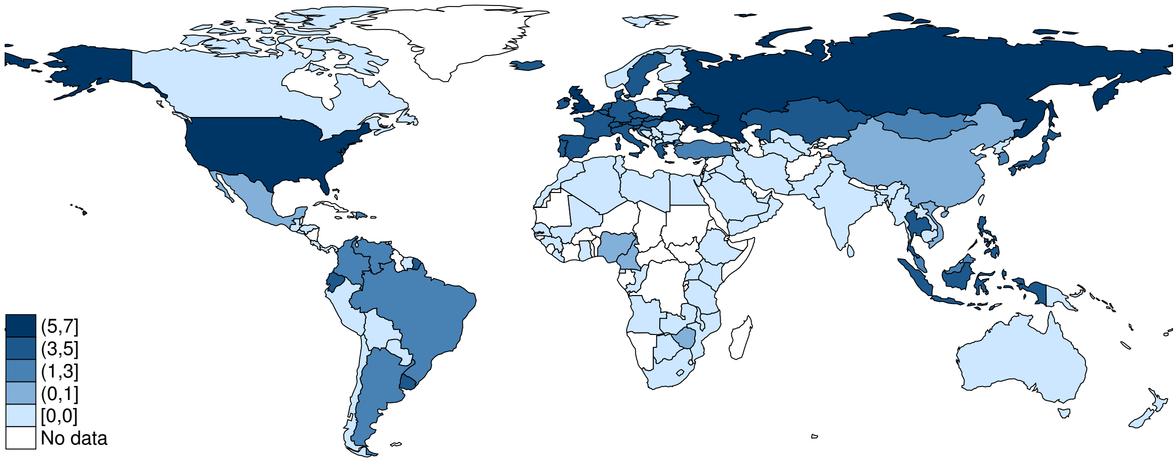
We conduct a comprehensive analysis of banks industry-specific lending strategies when faced with a banking crisis in a borrower country. We construct a metric to categorize banks according to the industry specialization of their international loan portfolio. For a large sample of cross-country syndicated loans, we find that banks specialize in certain industries and expand lending to those industries more than to the non-specialized ones in good times. When it comes to protecting their main industries in countries experiencing the crisis, industry specialization leads to a higher loan growth to firms from those industries at the intensive margin. Industry specialization becomes important for all firms within that industry after 6 months, when the coefficient of interest turns significant and implies 10% increase in lending associated with one standard deviation increase in industry specialization. This effect persists, with an upward trend, for at least 24 months.

Detailed loan-level data ensure identification through time-varying fixed effects on the firm level; Robustness tests show that it is unlikely that the results are driven by individual characteristics of the banks', and how quality of the firms, or bank-firm specific information that they have collected through previous interactions might affect the results. Our results indicate the positive aspect of lending concentration during crisis times as it countributes to increased monitoring skills of banks to discern heathy from non-healthy borrowers.

We come to important and novel conclusions in terms of spillover of banking crises across countries, and the role of industry specialization in those spillovers. We find that banks transmit negative shock to countries with no crisis in order to re-channel necessary funds to a country experiencing the crisis. However, specialization of banks' portfolio in one industry increases the resilience of those industries during a negative shock caused by financial crises abroad and shields these specialized industries from cross-border contagion – one standard deviation higher level of bank's industry specialization leads to an offset of negative effect on lending in connected countries. On the other hand, firms borrowing from banks less specialized in their industries might be more prone to shock transmission within and across countries.

2.6 Appendix

Figure A.3.1: Number of banking crisis years by country



Note: This figure shows the number of years with a banking crisis for each country. Banking crises are defined in Laeven and Valencia (2013). Darker colors show countries with more banking crisis years, lighter colors those with less.

Figure A.3.2: Distribution of banks' industry specialization

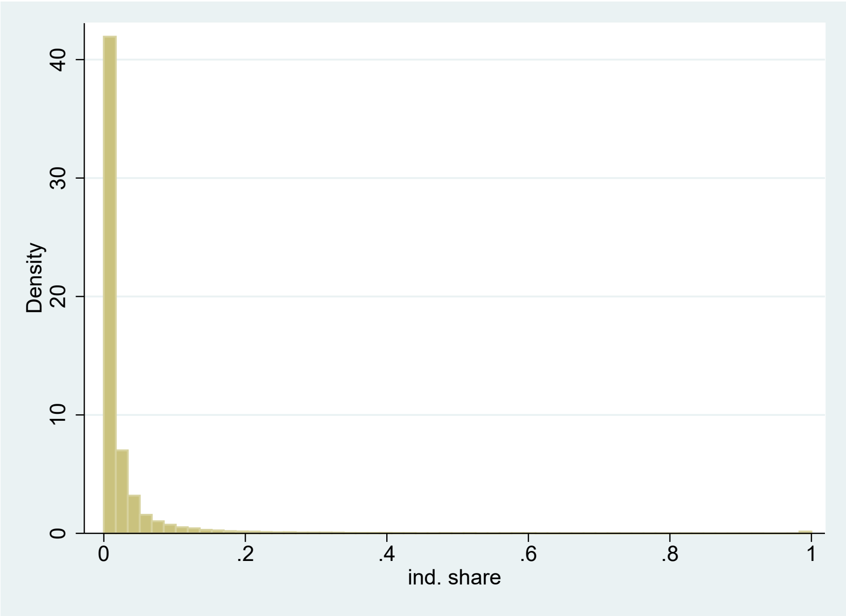
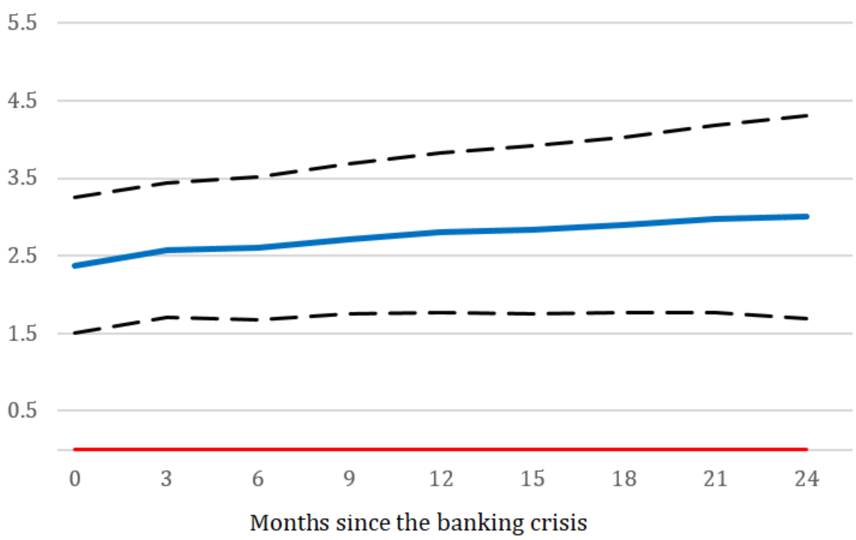


Figure A.3.3: Timing of the effect of industry specialization in connected countries



Note: This figure illustrates the timing and magnitude of the international spillover following a banking crisis in terms of industry specialization. The panels contain information on the interaction effect of the connected country and bank industry specialization. We plot the coefficients and 90% confidence bounds (dashed lines) for the interaction coefficients obtained from 9 separate estimations.

Table A.3.1: Robustness to multicollinearity: Spillover effects, industry level

	(1)	(2)	(3)
VARIABLES	log(loan)	log(loan)	log(loan)
Industry spec.	6.00***	5.14***	4.47***
	(0.22)	(0.20)	(0.30)
connected	-0.80***	-0.42***	-0.00
	(0.19)	(0.14)	(0.04)
Connected X Ind. spec.	5.70***	4.60***	1.48***
	(0.91)	(0.61)	(0.31)
Observations	430,460	427,875	428,617
R-squared	0.47	0.68	0.88
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Bank*Country*Industry FE	-		Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-country-industry-quarter level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to industry i in country c in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

Table A.3.2: Robusteness to multicollinearity: Spillover effects, loan level

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
Industry spec. (t-1)	5.76***	4.90***	4.46***	1.90***
	(0.35)	(0.30)	(0.39)	(0.17)
Connected	-0.17	-0.12	-0.20	0.01
	(0.14)	(0.11)	(0.15)	(0.01)
Connected X Ind. spec.	4.34***	3.08***	3.12***	0.30*
	(0.99)	(0.89)	(0.76)	(0.16)
Observations	578,370	519,276	195,295	575,788
R-squared	0.38	0.54	0.76	0.94
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-	-
Firm*Time FE	-	-	Yes	-
Bank*Firm FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-firm-quarter (loan) level for different levels of cluster-robust standard errors. The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

Table A.3.3: Robustness: loan level - exclusion of GFC

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
Banking crisis (BC)	-0.23**			-0.01
	(0.10)			(0.01)
Industry spec.	6.37***	5.26***	4.86***	1.93***
	(0.42)	(0.32)	(0.41)	(0.18)
BC X Industry spec.	-0.85**	-0.85	0.66	-0.02
	(0.42)	(0.55)	(0.95)	(0.11)
Observations	578,370	519,276	195,295	575,788
R-squared	0.38	0.54	0.76	0.94
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-	-
Firm*Time FE	-	-	Yes	-
Bank*Firm FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows regressions on the bank-firm-quarter (loan) level estimated on the subset of data excluding the time period coinciding with the Global Financial Crisis (2008-2010). The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *** p<0.01, ** p<0.05, * p<0.1

Table A.3.4: Robustness: spillovers, loan level - exclusion of GFC

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)	(4) log(loan)
Industry spec.	5.76***	4.90***	4.46***	1.90***
	(0.35)	(0.30)	(0.39)	(0.17)
Connected countries	-0.17	-0.12	-0.20	0.01
	(0.14)	(0.11)	(0.15)	(0.01)
Connected X Ind. spec.	4.34***	3.08***	3.12***	0.30*
	(0.99)	(0.89)	(0.76)	(0.16)
Observations	578,370	519,276	195,295	575,788
R-squared	0.38	0.54	0.76	0.94
Bank*Time FE	Yes	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-	-
Firm*Time FE	-	-	Yes	-
Bank*Firm FE	-	-	-	Yes
Clustered SE	Bank	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-firm-quarter (loan) level estimated on the subset of data excluding the time period coinciding with the Global Financial Crisis (2008-2010). The dependent variable is log of total outstanding loan volume by bank b to firm f in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

Table A.3.5: Robustness: industry level - exclusion of GFC

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)
Banking crisis (BC)	0.66***		-0.05
	(0.18)		(0.05)
Industry spec.	6.65***	5.56***	4.55***
	(0.28)	(0.23)	(0.31)
BC X Industry spec.	-0.34	-0.05	0.57***
	(0.37)	(0.30)	(0.18)
Observations	430,460	427,875	428,617
R-squared	0.46	0.68	0.88
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Bank*Country*Industry FE	-		Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows regressions on the bank-country-industry-quarter level estimated on the subset of data excluding the time period coinciding with the Global Financial Crisis (2008-2010). The dependent variable is log of total outstanding loan volume by bank b to industry i in country c in quarter t; *Banking crisis (BC)* is a dummy with value one during banking crises in the firm country, as defined in (Laeven2013); *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *** p<0.01, ** p<0.05, * p<0.1

Table A.3.6: Robustness: industry level - exclusion of GFC

VARIABLES	(1) log(loan)	(2) log(loan)	(3) log(loan)
Industry spec.	6.00***	5.14***	4.47***
	(0.22)	(0.20)	(0.30)
Connected	-0.80***	-0.42***	-0.00
	(0.19)	(0.14)	(0.04)
Connected X Ind. spec.	5.70***	4.60***	1.48***
	(0.91)	(0.61)	(0.31)
Observations	430,460	427,875	428,617
R-squared	0.47	0.68	0.88
Bank*Time FE	Yes	Yes	Yes
Country*Industry*Time FE	-	Yes	-
Bank*Country*Industry FE	-		Yes
Clustered SE	Bank	Bank	Bank

Note: This table shows spillover effects on the bank-country-industry-quarter level estimated on the subset of data excluding the time period coinciding with the Global Financial Crisis (2008-2010). The dependent variable is log of total outstanding loan volume by bank b to industry i in country c in quarter t; *Industry specialization* is measured as the ratio of loans granted by bank b to all borrowers of industry i in time period t relative to bank b's total lending granted in the same period, lagged by one period (quarter). *Connected countries* is a dummy variable which equals one for all non-crisis countries c' ($\neq c$), to which bank b is actively lending in t. *** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Bank Liquidity Regulation and Institutional Lending in the Syndicated Loan Market

3.1 Introduction

Today's financial markets are characterized by a rapidly increasing presence of non-bank financial institutions.[1] These developments have changed the structure of the credit market and the way it reacts to the change of macroeconomic policies and financial shocks. As non-banks remain outside of the regulatory perimeter, increasing macroprudential regulation of banks creates space for policy circumvention and further shift of lending activity from banks to non-banks.

[1] Non-banks are also referred to as Institutional investors in the syndicated loan market. This paper uses the two terms interchangeably.

Liquidity regulation, especially in the post Global Financial Crisis context, is aimed at reducing the exposure of banks to short-term wholesale funding and their ability to finance cash outflows in a scenario of stress, by requiring banks to hold more liquid assets relative to less stable sources of funding. This paper focuses on introduction of Liquidity Coverage Ratio (LCR) that requires banks to hold enough high-quality liquid assets (HQLA) to prevent a possible run on banks during a financial distress for a period of 30 day. As banks are required to decrease their reliance on certain sources of funding, such as the wholesale funding, this might adversely affect their lending potential. De Haan and Vermeulen (2017) find that wholesale funding shocks have significant effects on loan rates and credit supply, particularly of banks in stressed countries. They also find that loan growth of large banks that are typically more dependent on wholesale funding show relatively stronger responses to wholesale funding shocks. Therefore, although more stringent liquidity regulation can reduce the risk of bank runs and freezing of the interbank market, there is a risk of their negative impact on bank lending to the real economy and bank profitability.

Additionally, where policy has led to a contraction of lending activity, the non-bank financial sector has often stepped in to satisfy part of the remaining demand for credit. Several authors find that there are important compositional effects found in credit supply related to risk and regulatory arbitrage by non-banks and regulated banks (Elliott et al., 2020; Jiménez et al., 2017; Aiyar et al., 2016). By allowing for arbitrage, banking regulation has additionally contributed to more non-bank participation in the syndicated loan market (Irani et al., 2021). This paper estimates the average treatment effect on banks and non-banks from the introduction of the

LCR. To the best of my knowledge, no paper looks at the effect of LCR on potential substitution between banks and non-banks.

The empirical analysis is based upon a rich dataset of syndicated loans from Refinitiv LPC DealScan for the period between 2010 and 2020. For liquidity policy implementation I use IMF's database on Macroprudential Policy implementation. The methodology combines a difference in differences approach that exploits different timing in policy implementation with two way fixed effects, controlling for time invariant group unobservable characteristics (bank and firm) as well as group invariant time trends. The results are robust to the assumption of liquidity tightening as a one time quarterly shock. Although I find no substitution effect as there is no evidence that banks decrease lending volume, the evidence robustly suggests that liquidity tightening leads to an increase of 28% in institutional tranches within the loan packages. I propose two potential mechanisms for why the institutional tranches increase. As institutional tranches are carved from the same loan packages that consist of bank tranches, the lead arrangers might have an incentive for increasing the institutional tranches, which are priced higher and bear higher fees, to raise additional cash flows to satisfy the regulatory driven need for holding more liquid assets. This would hold particularity true for banks with existing liquidity constraints. Indeed, when estimating the model on sub-samples of banks with different levels of net cash flows, the effect persists only in the sub-sample of banks with low cash flows recorded in the previous period. On the other hand, institutional investors are indirectly incentivized to issue more loans thanks to policy induced increased liquidity of mortgage backed securities (MBS) that they use as a main source of collateral in raising the funds in repo market (Gete and Reher, 2018). As

LCR favors financial instruments deemed safer than others, certain MBS make the cut, making them more attractive to banks and raising their liquidity through increased trading, allowing non-banks to raise more funds through an increase of the value of their collateral. A detailed analysis of this potential mechanism is proposed by Gete and Reher (2018) and is beyond the scope of this paper.

This paper contributes to the literature on the impact of liquidity policies, and more generally, macroprudential policies, on the credit market. While capital regulation is associated with lower credit growth and smoother credit cycles (Akinci and Olmstead-Rumsey, 2018; Cerutti et al., 2017; Gómez et al., 2020; Jiménez et al., 2017), the literature on liquidity regulation focused more on monetary policy transmission and interbank market. Liquidity requirements cause long-term borrowing and lending rate as well as demand for long-term interbank loans to increase (Bonner and Eijffinger, 2016; Bonner, 2012). Bech and Keister (2017) show that due to higher reserve holdings, the demand for overnight loans goes down, driving the overnight interest rate down, while Rezende et al. (2020) find that liquidity regulation affects bank demand for term deposits in monetary policy operations. Banerjee and Mio (2015) find that banks adjusted the composition of both assets and liabilities, increasing the share of high quality liquid assets and non-financial deposits while reducing intra-financial loans and short-term wholesale funding.

The implications of a growing non-bank sector should be carefully monitored by the policymakers: unregulated non-bank financial sector allows for macroprudential policy circumvention, leading to a further increase in participation of non-banks in the financial market. This in turn implies a potential buildup of risk specific to non-banks. While in good times non-banks rely on regulated banks with whom they have long-term relationships to channel liquidity, they are severely constrained during times of marketwide stress since they cannot issue insured liabilities nor access central bank liquidity. Furthermore, as non-banks fund their liquidity mostly from short term money market funding, they play an important role in shock amplification when liquidity in the market freezes up, exacerbating asset devaluation through fire sale mechanisms (Muller et al., 2012). Therefore, it is important to understand how policies aimed at regulating banks might lead to alteration of non-bank lenders' behaviour and what are the implications for the stability of the system.

The rest of this paper is organized as follows: Section 2 gives an overview of liquidity policies since the Global Financial Crisis and how institutional lending developed over the same time period; Section 3 describes the data used for the empirical investigation, while Section 4 elaborates on the empirical strategy employed to address the main research questions; Section 5 presents the research findings while Section 6 provides concluding remarks.

3.2 Institutional Background

3.2.1 Global Financial Crisis and Basel III Framework

Following the GFC, much effort has been made in addressing the financial stability and the systemic risk. The Basel Committee on Banking Supervision (BCBS) has formulated a global regulatory framework on bank capital adequacy, stress testing, and market liquidity risk that has been internationally agreed upon. Basel III standards are minimum requirements that apply to internationally active banks. These standards are intended to strengthen bank capital requirements, increase bank liquidity and decrease bank leverage. The initial Basel III regulatory framework was published in 2010 and it was introduced introduced between 2013 and 2015. Most jurisdiction transposed the rules to their legislative frameworks by mid 2013 and the rules became effective from 2014.

When it comes to measures concerning liquidity, Basel III proposes two measures: Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). LCR addresses the systemic risk by requiring banks to hold a buffer of high-quality liquid assets (HQLA) high enough to prevent a possible run on banks during financial distress for a period of 30 days, providing the time for the central bank to step in and implement corrective measures to stabilize the financial system. LCR can be summarized by the following formula:

$$\frac{\text{Stock of HQLA}}{\text{Total net cash outflows over the next 30 calendar days}} \geq 100\% \tag{3.1}$$

HQLA are divided in three categories: Level 1 assets include cash, central bank reserves, central bank assets and sovereign debt. They have a zero haircut and must make up at least 60% of total HQLA, Level 2A assets cover government securities, covered bonds and corporate debt securities, have a 15% haircut and a maximum amount of 40%. Finally, Level 2B assets includes RMBS rated AA or higher, corporate or covered bonds rated A+ to BBB, corporate equity securities, have a 50% haircut and can make up to 15% of total HQLA. The net cash outflow number reflects assumptions about which deposits (liabilities) will leave the bank in a time of systemic stress. The proportion of deposits expected to exit is referred to as the run-off factor. The more stable the source of funding is perceived to be, the lower the run-off factor applied to it. Uninsured wholesale funding from financial institutions is considered the least stable and thus subject to the most severe run-off assumption of 100%.

Since 2015, countries have started to implement LCR, often with a gradual phase in over the several consecutive years until the full implementation of 100% of LCR. The rule applies to all banks uniformly.[2] In cases when the liquidity regulation has been phased in throughout several periods, we measure policy implementation since the first implementation of liquidity rules.

Additionally, while the rule is designed to strengthen the liquidity risk management of banks, it does not extend to institutional lenders in the market. Main reason for that is different liquidity structure of these entities, i.e. their non-deposit taking nature, meaning no access to one of the few sources of level 1 liquid assets, as defined in the regulation tailored for banks.

The second standard for funding liquidity within the Basel III framework is the Net Stable Funding Ratio (NSFR), which has been implemented since 2018 and is aimed at promoting resilience over a longer time horizon. The NSFR requires banks to maintain a stable funding profile in relation to the composition of their assets and off-balance sheet activities. A sustainable funding structure is intended

[2]Aldasoro and Faia (2016), for instance, propose that liquidity policies disproportionately burdens small and big banks and suggest that the requirements should be made more efficient in containing systemic risk with less burden to the economy if skewed towards systemically important banks. They find that systemic risk goes considerably down when liquidity requirements are skewed towards systemically important banks – with no change in aggregate liquidity requirements.

to reduce the likelihood that disruptions to a bank's regular sources of funding will erode its liquidity position in a way that would increase the risk of its failure and potentially lead to broader systemic stress. The NSFR limits over-reliance on short-term wholesale funding, encourages better assessment of funding risk across all on- and off-balance sheet items, and promotes funding stability. (Basel Committee on Banking Supervision, 2014)

3.2.2 Institutional Lending in the Syndicated Loan Market

The structure of the credit market globally has changed significantly over the last decades, with a growing portion of institutional investors, such as hedge funds, pension funds, mutual funds etc. Figure 1 shows the evolution of bank and institutional lending in the syndicated loan market in the last decade. Institutional investors started entering the syndicated loan market shortly after the introduction of loan ratings by Moody's and S&P in 1995 providing value-added information to potential non-bank syndicate participants. During the same time period, the development of the secondary loan sales market resulted in additional liquidity of syndicated loans which also attracted a growing number of institutional investors to enter this market (Nandy and Shao, 2008). Non-bank institutional lenders typically have higher required rates of return than banks, so they lend mostly to riskier borrowers in the market. The institutional lending is almost entirely concentrated in the leveraged segment of the market.[3] Between 2001 and 2007, annual institutional funding in highly leveraged loans went up from $32 billion to $426 billion, accounting for nearly

[3] A leveraged loan is a type of loan that is extended to companies that already have considerable amounts of debt or poor credit history, i.e. high leverage.

70% of the jump in total syndicated loan issuance over the same period (Ivashina and Sun, 2011). Institutional loans, typically Term loans B, have bullet repayment schedules and longer maturities, and are priced higher than the average bank loan.

Since 1990s there has been a growing use of "originate-to-distribute" model by banks in their corporate lending business – which refers to bank negotiating and then "distributing" the corporate loans they originated by syndicating loans, particularly to institutional investors. By adopting this model banks have been an important contributor to the growth of non-bank market participation, also referred to as the shadow banking system. Bord and Santos (2012) find that lead banks increasingly distributed their term loans by selling larger portions of them not only at the time of the loan origination, but also in the years after origination.

Another important contributor to the growth of institutional lenders is the post-crisis financial regulation: as banks became constrained with higher capital and leverage ratios, institutional investors stepped in to replace banks in providing corporate funding, attracted by the significantly higher returns on offer as a result of the shrinking lender base. Tightening capital requirements therefore spurs a surge in shadow banking activity (Acharya et al., 2013), that leads to an overall larger risk on the money-like liabilities of the formal and shadow banking institutions (Plantin, 2015). As bank loan demand continues to be constrained by regulatory reasons, these high returns continue to be an incentive for institutional investors, which are compensated for the credit risk they are taking on.

Table A.3.1: Loan characteristics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Loan tranche (USD mil.)	288.28	822.73	0.01	100000	162193
Loan package (USD mil.)	533.38	1592.07	0.01	100000	162193
Spread (pp)	293.53	169.65	0.15	990.00	77282
Maturity (years)	5.10	3.95	0.01	96.12	156177
Term loan $\in \{0,1\}$	0.56	0.50	0	1	162193
Revolver loan $\in \{0,1\}$	0.38	0.48	0	1	162193
Institutional loan $\in \{0,1\}$	0.10	0.30	0	1	162193
Cash flows (USD mil.)	53389.23	162373.80	0.1	7981823	12936

Note: This table shows summary statistics for all variables used in the analysis from the Refinitiv LPC Dealscan sample.

3.3 Data

3.3.1 Syndicated Loans

For the main analysis, this paper explores Refinitiv data on syndicated loans issued by banks worldwide. Syndicated lending constitutes a significant share of total lending; around one-third of total international lending is done through the syndicated loan market and it is an important source of financing in both developed and emerging economies (Cerutti et al., 2017). Syndicated loans are issued jointly by a group of banks and institutional lenders to a single borrower in order to mitigate the risk and take part in financial opportunities that may be too large for individual lenders. The lending syndicate includes at least one lead bank (also called lead arranger) and further participant banks. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to bigger borrowers. The average characteristics of loans in the sample are presented in Table A.3.1.

The respective database provides extensive information on syndicated loans at origin, including loan package amount, date, number of tranches, tranche amount, participating institutions and their individual commitments[4], maturity, spread as well as a set of borrower and lender characteristics. Importantly, the dataset contains identities of both lenders and borrowers necessary for a robust statistical identification of the model. The database also provides Moody's and S&P borrower credit ratings that contribute to the identification of leveraged submarket within the syndicated loan market. Namely, the leveraged market is defined by borrowers with either non-investment credit rating, or no rating and a spread over 200 points above LIBOR.

The database provides information on institutional lenders participation in the loan tranche. The "institutional flag" takes value 1 if institutional lenders participate in the loan, and 0 otherwise. Institutional lenders in the sample include mutual funds, insurance companies and pension funds. Figure A.4.1 shows the evolution of institutional tranches in syndicated lending compared to total lending in syndicated loan market in the sample. Over the sample period (2010-2019) institutional tranches almost tripled its share of total syndicated lending, from 8.3% in 2010 to 24.7% in 2017.

Table A.3.2 contrasts the characteristics of institutional tranches, to those of bank tranches. Institutional tranches are bigger in size and characterized by spreads almost twice as high as those of bank loans. Lim and Weisbach (2012) empirically

[4]Only a small fraction of the sample contains information on individual commitments, which presents a limitation in using this data for the analysis

Table A.3.2: Characteristics of bank loans (Panel A) and institutional loans (Panel B)

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A					
Loan tranche (USD mil.)	276.15	842.55	0.01	100000	146308
Loan package (USD mil.)	510.50	1626.04	0.01	100000	146308
Spread (pp)	260.14	150.14	0.15	990.00	63712
Maturity (years)	5.01	4.07	0.01	90.31	140743
Term loan $\in \{0,1\}$	0.519	0.50	0	1	146308
Revolver loan $\in \{0,1\}$	0.42	0.49	0	1	146308
Panel B					
Loan tranche (USD mil.)	400.08	599.27	0.33	15375.17	15885
Loan package (USD mil.)	744.15	1216.03	0.62	38000	15885
Spread (pp)	450.28	168.16	7.00	983.00	13570
Maturity (years)	5.99	2.49	0.08	96.12	15434
Term loan $\in \{0,1\}$	0.97	0.17	0	1	15885
Revolver loan $\in \{0,1\}$	0.03	0.17	0	1	15885

Note: This table shows summary statistics for bank tranches and institutional tranches within the sample.

show that institutional tranches, even within the same loan package and same characteristics, tend to be priced higher than bank only tranches. They argue that non-bank institutional lenders typically have higher required rates of return than banks, so the arranger has to offer a higher spread to attract the non-bank institution. Additionally, Table A.4.1 shows that, given the reported credit rating, institutional investors concentrate in the non-investment grade section, while the vast majority of investment grade borrowers borrow from traditional banks.

For the analysis, the data is aggregated by the lead arranger. The reason is twofold – first, there is not enough information on individual commitments of syndicate participants, and splitting the loan volume equally among listed lenders would not account for typically significant differences in loan participation, but more importantly – the lead arrangers are the ones who decide on the loan syndication process and allocation of tranches among banks and institutional investors. By virtue of the commonly used "market flex" provision, syndicate arrangers are entitled to unilaterally adjust the pricing, structure, terms and possibly the total financing amount to the extent necessary to ensure its successful syndication. Secondly, the increase is expected to happen within existing loan packages, in which case all the relevant information is preserved when identifying the loan volume changes solely through lead arranger. The dataset is collapsed to the borrower-arranger-tranche-month level before merging with macro prudential policy measures.

3.3.2 Macroprudential Policy Measures

The syndicated loan data is matched with the IMF's Integrated Macroprudential Policy (iMaPP) Database that provides a comprehensive landscape of macroprudential policy, covering all instruments discussed in IMF (2019) for 134 countries from 1990-2016. For the purpose of the research question, the analysis focuses on Liquidity tightening binary variable that takes value one for every time period a country has put a new liquidity regulation in place. The complete variable of interest captures the introduction of liquidity tightening measures between 2010 and 2019 in 47 countries, exploring different timings and implementation schedules. In most cases, the countries have implemented the introduction of LCR in phases, setting the regulatory threshold, for instance, to the level of 60% and increasing it yearly by 10% until the full implementation of 100%. I assign treatment only to the first implementation, assuming that banks become constrained by the policy at the time of its first implementation and adapt over a longer period of time. Despite the database recording each of this increase as a separate liquidity tightening, looking at each of these increase as a new policy shock would be a misrepresentation in the author's view.

The most significant aspect of liquidity regulation during this period captureb by the database is the implementation of LCR. However, the database covers occasional introduction of Liquidity tightenings that are not directly related to the implementation of Basel III regulation. I exclude these occurrences in order to focus on the implementation of the LCR. The data is recorded at a monthly frequency, which corresponds to the level of aggregation used for the syndicated loans.

3.4 Hypothesis and Empirical Design

The main hypothesis of this paper is that tightening of liquidity requirements leads to significant redistributional effects between regulated and unregulated actors in the financial market. More precisely, as banks are forced to decrease reliance on wholesale funding, this might be transposed to a constraint of their lending potential. Non-banks, on the other hand, have been in several cases found to profit from bank regulation, by being able to circumvent it, providing extra loan volume to substitute for the banks' decrease in lending.

To estimate the size of this potential effect, this paper employs complementary quasi-experimental approaches, including difference-in-differences estimation and two way fixed effects. The standard bank and year fixed effects framework uses variation in the timing of policy implementation across jurisdictions to identify the effects of the new liquidity requirements. Time fixed effects trace out the common time trend, while the group fixed effects, in this case bank and firm fixed effects, control for unobserved group characteristics. The DiD estimation equation for testing the hypothesis of this paper is as follows:

$$\begin{aligned} Log(loan)_{b,f,t} &= \beta_1 Liquidity\_T_{b,t} + \beta_2 Institutional_{b,f,t} \\ &+ \beta_3 Liquidity\_T_{b,t} \times Inst._{b,f,t} + \phi_b + \theta_f + \gamma_t + \varepsilon_{b,f,t} \end{aligned} \tag{3.2}$$

Where $Log(loan)$ represents loan development at the tranche level. The predictors include $Liquidity\_T_{b,t}$ - a dummy variable that takes value 1 if the bank b has already implemented liquidity requirements, $Institutional_{b,f,t}$ - a dummy variable that takes value one if the loan tranche of bank b to firm f in time t is flagged as an institutional tranche, and the interaction term $\beta_3 Liquidity\_T_{b,t} \times Inst._{b,f,t}$ that represents the treatment of interest and identifies the growth of institutional tranches after the liquidity requirements were implemented. ϕ_b, θ_f and γ_t represent bank, firm and time fixed effects. I explore different combinations of fixed effects to examine the importance of different unobserved factors of different groups in transmission of the effect. One of the most restrictive specifications uses firm fixed effects, in addition to bank fixed effects, to control for firm specific unobservable factors, by comparing borrowing of one firm from two or more different banks. Alternatively, to allow for higher degrees of freedom, I replace firm fixed effects with industry-country fixed effects, assuming the homogenous behaviour of firm demand in a specific industry i in a country c.

The easiest ways for banks to increase the volume of institutional lending is through existing loan facilities, with no additional costs related to loan syndication. In the last specification I control for loan package fixed effects to estimate the changes within the existing loan packages. I then re-estimate the model on the sub-sample of leveraged borrowers to show which part of the effect is concentrated in the leveraged market. As the level of treatment is the country level, the standard errors for all specifications are clustered on country-time level to account for correlation in standard errors at the country level, before and after the treatment. The results are robust to alternative assumptions about the correlation of the errors, such as country level and bank level.

Difference-in-differences designs rely on the assumption that the important unmeasured variables are either time-invariant group attributes or time-varying factors that are group invariant. Together, these restrictions imply that the time series of outcomes in each group should differ by a fixed amount in every period and should exhibit a common set of period-specific changes. In applied work, the most difficult task is evaluating the credibility of the common trends assumption (Wing et al., 2018). Graph A.4.2 shows the trends of institutional loan volume for the two largest treatment groups that implemented the policy at two different time periods: US (January 2015) Euro Zone countries (October 2015). These jurisdictions together account for almost 2/3 of institutional lending in the dataset. Conceptually, we expect the co-movement of institutional loan volumes across different countries due to some of the important underlying reasons for the recent evolution of institutional lending being globally true: banks' across all jurisdictions face similar pressures from tightening regulation and central bank stress tests, opening the space for institutional investors' in providing corporate funding.

The DiD design is meant to control for the unmeasured confounders across groups and time periods even though the underlying variables are not measured explicitly. A potential weakness of a DiD method is a potential spillover effect of implemented policy to seemingly untreated groups. This would be the case if a bank b lends to firm f in Germany which didn't yet implement the liquidity requirements in observed period and is considered untreated, while the bank's b parent is located in the United States that did require banks to implement the liquidity ratio. As Basel Framework is designed to be applied to internationally active banks on a fully consolidated basis, meaning that it applies to any holding company that is the parent entity within a banking group to ensure that it captures the risks of the banking group as a whole, I group the effect at the level of bank parent company to adequately separate treated from untreated units.

3.5 The impact of Liquidity Requirements Introduction on Credit Growth

In order to evaluate the effect of liquidity tightening on credit allocation between banks and non-banks this paper estimates the model specified in Equation 3.2, using a difference-in-differences estimator. The results are presented in Table A.3.3. To explore the robustness of the results and contrast the importance of different

Table A.3.3: Impact of liquidity tightening policy introduction on institutional loans

VARIABLES	(1) Δ% lending	(2) Δ% lending	(3) Δ% lending	(4) Δ% lending	(5) Leveraged loans
Liquidity_T	-0.02	0.01	0.03	0.04	-0.04
	(0.04)	(0.03)	(0.03)	(0.11)	(0.03)
Institutional	0.43***	0.55***	0.72***	0.92***	0.81***
	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Liquidity_T X Institutional	0.16***	0.16***	0.22***	0.28***	0.20***
	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)
Observations	138,798	136,151	122,110	79,869	68,124
R-squared	0.25	0.45	0.77	0.78	0.74
Bank FE	Yes	Yes	Yes	-	Yes
Time FE	Yes	Yes	Yes	-	Yes
Industry-Country FE	-	Yes	-	-	-
Firm FE	-	-	Yes	-	Yes
Loan package FE	-	-	-	Yes	-

Note: The table shows estimated regression coefficients for equation 1. The dependent variable is log of loan volume by bank b to firm f in month t; *Liquidity_T* is a treatment variable that takes value 1 if liquidity tightening policy has been implemented in the bank's b country; *Institutional* is a binary variable that flags the institutional tranches within the loan package, The interaction term *Liquidity_TXInstitutional* identifies institutional tranches following the liquidity tightening introduction to isolate impact specific to the institutional loans. The regressions are at monthly frequency. Columns 1-4 present results from estimations employing different combinations of fixed effects. Column 5 reestimates the model with most demanding fixed effects on the subsample of loans characterized as the leveraged submarket. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

unobserved factors, the model is saturated with different combinations of fixed effects in each column. Column 1 presents results of a model using only bank-time fixed effects, absorbing the unobservable heterogeneity across banks. Before controlling for the unobserved demand factors, the estimated impact of liquidity tightening introduction institutional lending is a 16% increase. The impact of the policy on bank loans, however, is not statistically or economically significant in any of the model specifications.

Column 2 introduces country-industry-time fixed effects in addition to previous specification in order to control for demand factors under assumption that the demand of all firms in an industry i in a country c behaves similarly. Durdu and Zhong (2019) find that sectoral shocks affecting the balance sheets of firms who borrow from the financial sector are an important factor for the business cycle frequency fluctuations in bank and nonbank credit growth. Under this assumption, the effect of liquidity tightening on institutional lending is comparable to the one obtained when including only bank fixed effects and amounts to 16%.

Column 3 controls for firm unobserved characteristics by introducing the most restrictive specification of the model that includes firm fixed effects, in addition to banks and time fixed effects, and compares borrowing of firm f from several borrowers at the same time period t, similar to the methodology introduced by Khwaja and Mian (2008). When controlling for firm unobservable factors, the impact of liquidity tightening introduction on institutional loan tranches increases to a 28%. Contrasting this finding to the one in Column 1, including firm fixed effects contributes to fully identifying the impact, indicating that firm specific unobservable characteristics play a significant role in transmission of liquidity tightening implementation to institutional lenders' credit supply. As institutional tranches are issued to riskier borrowers, this market segment has weaker borrowers, muting part of the effect on the aggregate; however, when controlling for firm characteristics, there is a 28% increase in institutional lending as a consequence of the policy.

Given the fixed costs of borrowers' quality monitoring, the easiest way to increase the institutional tranches with no extra cost related to syndication of the loan or screening the borrower is to increase the institutional tranche within the existing loan package. Such behavior is further facilitated by market flex provision that is designed to give arrangers and underwriters some flexibility as to the terms of a financing following the signing of the relevant facility agreement, allowing for change of pricing of the loan and shifting amounts between various tranches of the loan. Column 4 presents the results of an estimation that includes loan package fixed effects and compares the growth of institutional tranches to bank tranches within the same loan package. Indeed, the impact is almost identical to the one found in the previous specification, indicating that the increase of institutional loan volume happens within the existing loan package.

Finally, in order to underline the fact that most of the described activity takes place in the leverage sub-market, comprised of leveraged borrowers which are defined by either non-investment grade credit rating or no rating with a spread higher than 200 points above LIBOR, the last column restricts the sample to those borrowers and uses bank, firm and fixed effect specification to compare the effect to Column 3. The effect is almost identical, supporting the fact that the increase of institutional loans happens in the risky segment of the syndicated loan market and revealing the potential implications for buildup of vulnerabilities in the financial market and subsequent policy implications.

3.5.1 Proposed Mechanism

With finding no effect of Liquidity tightening on bank lending, I rule out the substitution effect between banks and non-banks. This is in line with findings of Bonner (2012); Bonner and Eijffinger (2016); Banerjee and Mio (2015); Roulet (2018) that do not find the direct effect on lending growth to overall non-financial sector. The results show that institutional tranches increase in their volume compared to the bank tranches within the same loan package after the implementation of Liquidity tightening. Institutional tranches, structured as Term loan B, are not only priced higher, but have a lower amortization of the principal than Term Loans A (bank tranches) leading to higher interest payments. The interest is paid in cash. Therefore the institutional tranches generate a higher cash inflow from interest. With these considerations in mind, I argue that lead banks profit from these features of institutional tranches, following the "originate-to-distribute" model, to generate more cash inflows than they would do with bank tranches. This hypothesis is tested in two ways: First, in order to increase the size of institutional tranches they would have to attract institutional investors by offering higher return, thus, raising the spread offered on the institutional tranche. Second, I expect to see this behavior to be specific to banks with prior liquidity constraints, i.e. low level of cash inflow in previous period.

I estimate the model specified in Equation 3.2 substituting loan growth with all in drawn spread as a dependent variable. All-in-drawn spread includes the base rate spread and facility, upfront, utilization or fronting fee. Table A.3.4 provides results that all in drawn spread indeed increases for institutional tranches after the implementation of liquidity tightening. The first two column estimate the impact on level all-in-drawn spread, while columns 3 and 4 provide the impact on relative growth of the spread. As maturity could be different among tranches and contribute to the differences in the pricing of institutional versus bank tranches, I include the maturity of the tranche as a control variable. In addition to institutional tranches

Table A.3.4: The impact of liquidity tightening on all-in-drawn spread

VARIABLES	(1) Spread	(2) Spread	(3) Log(Spread)	(4) Log(Spread)
Liquidity_T	-2.84	-2.94	-0.01	-0.01
	(16.18)	(15.87)	(0.03)	(0.03)
Institutional	54.49***	47.10***	0.13***	0.11***
	(4.24)	(4.10)	(0.01)	(0.01)
Liquidity_T X Institutional	23.28***	21.94***	0.06***	0.06***
	(5.93)	(5.82)	(0.01)	(0.01)
Maturity		6.65***		0.02***
		(1.02)		(0.00)
Observations	42,652	42,286	42,652	42,286
R-squared	0.88	0.89	0.94	0.94
Loan package FE	Yes	Yes	Yes	Yes

Note: The table shows estimated regression coefficients for equation 2. The dependent variable is the all-in-drawn spread on a loan tranche level, in levels (Column 1 and 2) and growth rates (Column 3 and 4) ; *Liquidity_T* is a treatment variable that takes value 1 if liquidity tightening policy has been implemented in the bank's b country; *Institutional* is a binary variable that flags the institutional tranches within the loan package, The interaction term *Liquidity_TXInstitutional* identifies institutional tranches following the liquidity tightening introduction to isolate impact specific to the institutional loans. The regressions are at monthly frequency. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

being priced 11% higher than the bank tranches within the same loan package, the introduction of Liquidity tightening leads to additional 6% increase in their price. Therefore, following the liquidity tightening, lead arrangers offer even higher premiums on institutional tranches in order to attract institutional investors.

Next, to support the hypothesis that banks increase institutional tranches issuance within their loan packages as a means to address their liquidity needs, we split the sample to three sub-samples of banks aggregated by their level of cash flows in the latest fiscal period.[5] I estimate the Equation 3.2 on all three samples separately

[5]Where this information is available, which represents only a fraction of the sample

and present the results in Table A.3.5. If this hypothesis on proposed mechanism is valid, than the banks with limited cash flows, and therefore constrained in terms of liquid holdings, are expected to lead this increase in institutional tranches issuance. Table A.3.5 shows the result of the estimation performed on three individual sub samples of banks - those with low, median and high previous net cash flows.[6] Indeed, only in the sub sample of banks with constrained cash flows the effect is statistically significant and comparable in magnitude to the one found when performing the estimation on the full sample. The size and significance of coefficients in sub-samples of banks with higher cash flows goes considerably down, while it loses significance completely when accounting for within loan fixed effects.

The second aspect of the increased activity of institutional lenders in the financial market concerns their incentive to provide more loans to firms. Apart from already notable upward trend in non-bank lending activity, the policy introduction leads to additional uptake in their lending volume. The possible explanation lies in the general equilibrium effect of the policy as described by Gete and Reher (2018). They propose a general equilibrium channel through which the LCR introduction affects the growth of non-bank activity through increased liquidity of MBS that are favored by the prescribed LCR ratio. LCR introduction affects the growth of non-bank activity through increased liquidity of MBS that are favored by the prescribed LCR ratio. Namely, the LCR High quality liquid assets (HQLA) include assets such as RMBS, which leads to an increase in demand for these assets and their liquidity. The increased liquidity on the other hand, leads to the lower funding costs of non-banks

[6] Cash flows are defined in the database as net income from total operations minus preferred dividends plus depreciation

Table A.3.5: The role of cash flows in the impact of liquidity tightening policies

VARIABLES	(1) Low CF	(2) Low CF	(3) Medium CF	(4) Medium CF	(5) High CF	(6) High CF
Liquidity_T	0.05	-0.20	0.12*	-0.15	0.05	-0.05
	(0.06)	(0.89)	(0.06)	(0.38)	(0.04)	(0.15)
Institutional	0.90***	1.04***	0.80***	1.03***	0.80***	0.98***
	(0.12)	(0.15)	(0.08)	(0.12)	(0.08)	(0.12)
Liquidity_T X Institutional	0.29***	0.35***	0.15**	0.08	0.10*	0.10
	(0.09)	(0.13)	(0.07)	(0.07)	(0.06)	(0.06)
Observations	31,565	21,471	32,677	19,146	32,381	21,859
R-squared	0.75	0.74	0.81	0.81	0.78	0.79
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	-	Yes	-	Yes	-
Loan package FE	-	Yes	-	Yes	-	Yes

Note: The table shows estimated regression coefficients for baseline model estimated on subsamples of banks with low (Columns 1 and 2), medium (Columns 3 and 4) and high cash flows (Columns 5 and 6). The dependent variable is log of loan volume by bank b to firm f in month t; $Liquidity_T$ is a treatment variable that takes value 1 if liquidity tightening policy has been implemented in the bank's b country; $Institutional$ is a binary variable that flags the institutional tranches within the loan package, The interaction term $Liquidity_T X Institutional$ identifies institutional tranches following the liquidity tightening introduction to isolate impact specific to the institutional loans. The regressions are at monthly frequency. Columns 1, 3 and 5 present results from estimations employing bank, time and firm fixed effects. Columns 2, 4 and 6 present estimations including within loan package fixed effects. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

that rely on repo markets for liquidity using Mortgage Backed Securities (MBS) as collateral. As the value of their collateral goes up, the cost of their credit lines goes down, leading to a greater funding possibilities of non-banks and subsequently increase their potential for loan provision. Detail investigation into this mechanism is beyond the scope of this paper and should be addressed future research in this area.

3.5.2 Robustness to Alternative Policy Related Shocks

As markets are driven by expectations, the first robustness test examines whether the behavior of banks is sensitive not only to the implementation of liquidity tightening, but to their announcement in each jurisdiction. Table A.4.2 provides results of such specification. The variable *Announcement* captures the period from the date of announcement until the date of implementation of liquidity tightening. The structure of fixed effects by columns is identical as the one in Table A.3.3. There is no evidence that the announcement of liquidity tightening policies leads to an increase in institutional lending. The coefficients of the interaction term *Announcement X Institutional* that isolates the effect of the policy announcement on bank and institutional loan volume is not significantly different than zero in any specification of the model.

Since many policies within a Basel III framework, in particular capital regulation, have been shown to have adverse effect on credit activity, in order to rule out that the identified effect is a consequence of some other macroprudential policy introduced around the same time, Table A.4.3 and A.4.4 shows the robustness of our results to introduction of capital regulation as well as adoption of Basel III framework itself. Table A.4.3 shows that, when introducing the variable on implementation of Basel 3 related higher capital standards, the impact of liquidity policies remains robust across all specifications, with coefficients comparable in significance and magnitude to those in the baseline specification. As expected, the introduction of tighter capital regulation has an overall negative effect on lending. When it comes to the capital requirements related substitution between banks and non banks, the substitution effect is recorded in the column that estimates the model on the sub sample of leveraged borrowers, which is expected as banks are incentivized by the regulation to move away from riskier borrowers while institutional investors concentrate their lending in the riskier segment of the market. Finally, Table A.4.4 shows that Basel III introduction is associated with a negative growth of bank lending overall, but not within the loan package, while it shows no impact on institutional lending volume at all. The impact of Liquidity policies on overall and institutional lending is robust to the inclusion of both policy shocks analyzed in this section.

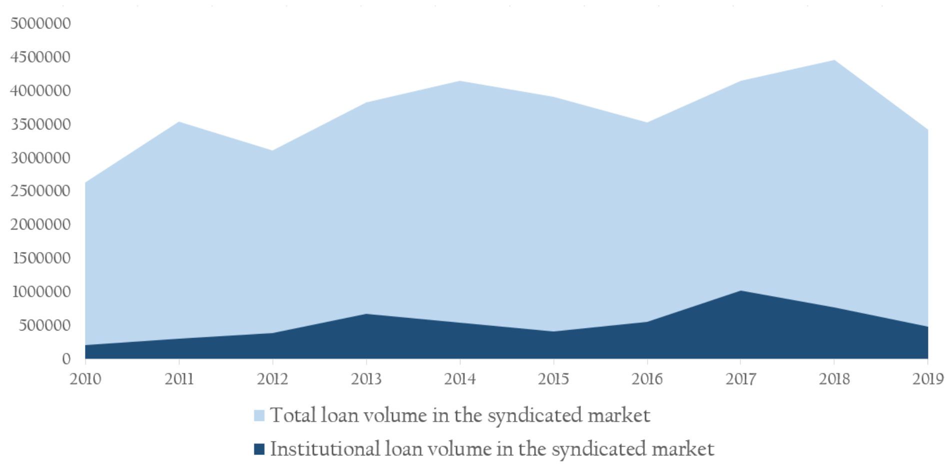
3.6 Conclusion

This paper investigates how liquidity tightening policies affect the role of non-bank lending in the syndicated loan market. While banks' lending to the non-financial sector does not change in response to liquidity tightening, the evidence shows that institutional lending increases by 28%. This paper argues that the main reason for such behavior of banks is the income generated from interest and fees incurred from originating, arranging and underwriting such loan facilities. As institutional tranches are priced higher and structured in a way to generate higher cash flows, the lead banks become incentivized to increase volume of tranches issued for institutional investors. The observed increase happens mostly within existing loan packages, avoiding the costs related to loan syndication. To attract institutional investors, they further raise the spread on institutional tranches. To support the hypothesis that banks increase institutional tranches within their loan packages as a means to address their liquidity needs, we show that this effect is significant mostly for the sub-sample of banks with previously low cash flows, as opposed to those banks that recorded higher cash flows in the previous fiscal period. Additionally, institutional investors profit indirectly from the regulation-driven increase of liquidity of securities they most often use as collateral, leading to their greater access to borrowing, and thus, greater lending supply.

Understanding how macroprudential policy interacts with both regulated and unregulated actors in the financial markets represents an important policy objective in order to continue shaping them in the most efficient way. Macroprudential policies often contribute to non-bank presence in the financial market, either through lending substitution or other mechanisms like the one discussed in this paper. This does not only affect the way the markets react to policies, but also highlights the need to examine the financial stability risks arising from the unregulated segment of financial markets. Rethinking macroprudential policies design to account for non-bank financial intermediaries represent an acute challenge, given their increasing market participation and the role in shock propagation in times of market-wide stress.

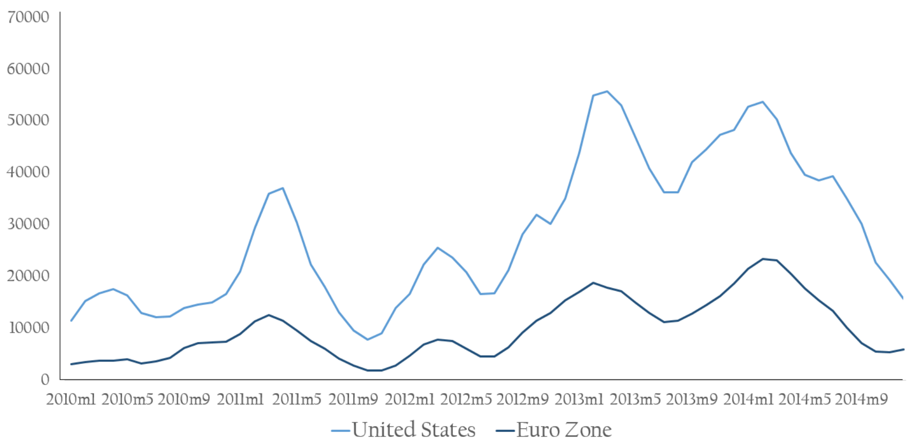
3.7 Appendix

Figure A.4.1: Evolution of loans in syndicated loan market



Note: This figure shows the evolution of total loan volume and institutional loan volume in the syndicated loans market within the sample over the observed period. Institutional loans are a part of the total loans.

Figure A.4.2: Trends of institutional loans in two major jurisdictions



Note: This figure shows the evolution of institutional loans in two major jurisdictions that account for 2/3 of institutional lending in the sample, prior to liquidity tightening introduction.

Table A.4.1: S&P credit rating for firms borrowing from banks (Panel A) and non-banks (Panel B)

Bank loans	**Frequency**	**Percent**	**Cumulative**
Prime	63	0.32	0.32
High grade	709	3.62	3.95
Upper medium grade	3,041	15.55	19.49
Lower medium grade	6,439	32.92	52.41
Non-investment grade	4,442	22.71	75.12
Highly speculative	4,447	22.74	97.86
Substantial risk	322	1.65	99.50
Total	19,560	100	
Extremely speculative	97	0.50	100.00
Prime	1	0.02	0.02
High grade	2	0.03	0.05
Upper medium grade	14	0.24	0.29
Lower medium grade	153	2.65	2.94
Non-investment grade	1,345	23.27	26.22
Highly speculative	3,883	67.19	93.41
Substantial risk	314	5.43	98.84
Extremely speculative	67	1.16	100.00
Total	5,779	100	

Note: This table shows distribution of borrowers by banks and non-banks based on available credit ratings.

Table A.4.2: Impact of liquidity tightening policy announcement on institutional loans

VARIABLES	(1) Δ% lending	(2) Δ% lending	(3) Δ% lending	(4) Δ% lending
Announcement	-0.03	-0.01	-0.03	-0.08
	(0.03)	(0.03)	(0.03)	(0.05)
Institutional	0.52***	0.64***	0.84***	1.06***
	(0.10)	(0.05)	(0.05)	(0.14)
Announcement X Institutional	0.03	-0.05	-0.01	0.04
	(0.07)	(0.03)	(0.03)	(0.06)
Observations	138,798	136,151	122,110	79,869
R-squared	0.25	0.45	0.77	0.78
Bank FE	Yes	Yes	Yes	-
Time FE	Yes	Yes	Yes	-
Industry-Country FE	-	Yes	-	-
Firm FE	-	-	Yes	-
Loan package FE	-	-	-	Yes

Note: The table shows estimated regression coefficients for the baseline model by using the policy announcement dates as treatment variable. The dependent variable is log of loan volume by bank b to firm f in month t; *Announcement* is a treatment variable that takes value 1 if liquidity tightening policy has been announced in the bank's b country; *Institutional* is a binary variable that flags the institutional tranches within the loan package, The interaction term $Liquidity\_TXAnnouncement$ identifies institutional tranches following the liquidity tightening announcement to isolate impact specific to the institutional loans. The regressions are at monthly frequency. Columns 1-4 present results from estimations employing different combinations of fixed effects. Column 5 reestimates the model with most demanding fixed effects on the subsample of loans characterized as the leveraged submarket. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.4.3: Robustness to Basel III capital regulation adoption

VARIABLES	(1) Δ% lending	(2) Δ% lending	(3) Δ% lending	(4) Δ% lending
Liquidity_T	-0.05	-0.01	0.02	0.05
	(0.05)	(0.04)	(0.03)	(0.11)
Institutional	0.42***	0.56***	0.71***	0.90***
	(0.04)	(0.03)	(0.03)	(0.04)
Liquidity_T X institutional	0.16***	0.15***	0.23***	0.31***
	(0.04)	(0.04)	(0.03)	(0.05)
Capital_T	-0.12***	-0.09***	-0.04**	0.00
	(0.03)	(0.03)	(0.02)	(0.08)
Capital_T X Institutional	0.06	0.00	0.07	0.14
	(0.06)	(0.06)	(0.04)	(0.09)
Observations	138,798	136,151	122,110	79,869
R-squared	0.25	0.45	0.77	0.78
Bank FE	Yes	Yes	Yes	-
Time FE	Yes	Yes	Yes	-
Industry-Country FE	-	Yes	-	-
Firm FE	-	-	Yes	-
Loan package FE	-	-	-	Yes

Note: The table shows estimated regression coefficients for equation 1 augmented by the Capital tightening implementation variable and its interaction with the institutional flag. The dependent variable is log of loan volume by bank b to firm f in month t; $Liquidity_T$ is a treatment variable that takes value 1 if liquidity tightening policy has been implemented in the bank's b country; *Institutional* is a binary variable that flags the institutional tranches within the loan package, The interaction term $Liquidity_T X Institutional$ identifies institutional tranches following the liquidity tightening introduction to isolate impact specific to the institutional loans. *Capital_T* is a dummy variable that indicates introduction of Basel 3 framework in bank countries' jurisdictions. To avoid multicollinearity, its time horizon is limited to the implementation of Liquidity regulation. The interaction term $Capital\_TXInstitutional$ estimates the effect of Capital tightening introduction on institutional loans. The regressions are at monthly frequency. Columns 1-4 present results from estimations employing different combinations of fixed effects. Column 5 reestimates the model with most demanding fixed effects on the subsample of loans characterized as the leveraged submarket. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.4.4: Robustness to Basel III framework adoption

VARIABLES	(1) Δ% lending	(2) Δ% lending	(3) Δ% lending	(4) Δ% lending
Liquidity_T	0.09	0.12**	0.08**	-0.02
	(0.07)	(0.05)	(0.03)	(0.07)
Institutional	0.44***	0.55***	0.71***	0.94***
	(0.08)	(0.07)	(0.07)	(0.10)
Liquidity_T X Institutional	0.16**	0.13**	0.18***	0.30***
	(0.07)	(0.06)	(0.05)	(0.09)
Basel 3	-0.16**	-0.15**	-0.12***	0.08
	(0.07)	(0.06)	(0.04)	(0.08)
Basel 3 X Institutional	-0.07	0.07	0.11	-0.08
	(0.17)	(0.09)	(0.07)	(0.11)
Observations	161,718	158,899	142,359	93,080
R-squared	0.25	0.44	0.77	0.77
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry-Country FE	-	Yes	-	-
Firm FE	-	-	Yes	-
Loan package FE	-	-	-	Yes

Note: The table shows estimated regression coefficients for equation 1 augmented by the Basel 3 implementation variable and its interaction with the institutional flag. The dependent variable is log of loan volume by bank b to firm f in month t; $Liquidity_T$ is a treatment variable that takes value 1 if liquidity tightening policy has been implemented in the bank's b country; $Institutional$ is a binary variable that flags the institutional tranches within the loan package, The interaction term $Liquidity_T X Institutional$ identifies institutional tranches following the liquidity tightening introduction to isolate impact specific to the institutional loans. $Basel3$ is a dummy variable that indicates introduction of Basel 3 framework in bank countries' jurisdictions. To avoid multicollinearity, its time horizon is limited to the implementation of Liquidity regulation. The interaction term $Basel3XInstitutional$ estimates the effect of Basel III introduction on institutional loans. The regressions are at monthly frequency. Columns 1-4 present results from estimations employing different combinations of fixed effects. Column 5 reestimates the model with most demanding fixed effects on the subsample of loans characterized as the leveraged submarket. Standard errors are clustered at Country X Time level. Robust standard errors are presented in parentheses *** p<0.01, ** p<0.05, * p<0.1

Country	Month of implementation	Year of implementation
Finland	June	2010
New Zealand	July	2011
Peru	December	2012
Sweden	January	2013
Costa Rica	August	2013
Qatar	January	2014
China	December	2014
United States	January	2015
Switzerland	January	2015
Taiwan	January	2015
Australia	January	2015
Argentina	January	2015
Saudi Arabia	January	2015
Turkey	January	2015
Hong Kong	January	2015
Singapore	January	2015
South Korea	January	2015
South Africa	January	2015
Japan	March	2015
Germany	October	2015
Italy	October	2015
United Kingdom	October	2015
Spain	October	2015
Portugal	October	2015
Netherlands	October	2015
Belgium	October	2015
France	October	2015
Greece	October	2015
Denmark	October	2015
Ireland	October	2015
Austria	October	2015
Croatia	October	2015
Czech Republic	October	2015
Romania	October	2015
Poland	October	2015
Slovenia	October	2015
Slovak Republic	October	2015
Luxembourg	October	2015
Norway	October	2015
Indonesia	January	2016
Malaysia	January	2016
Mexico	January	2016
Thailand	January	2016
Russian Federation	January	2016
Pakistan	November	2016
Philippines	March	2016

Chapter 4

Model Selection Methods for Financial Stress Testing [1]

4.1 Introduction

Model selection methodologies – as one element in the field of machine learning – are widely used in many scientific disciplines, including geophysics, economics, finance, network analysis, image recognition, and others, and keep gaining in relevance amid the accumulation of ”big data”. They serve to help identify a subset of relevant predictors for some target variable, to help corroborate (accept, reject, refine) theories as well as for designing econometric models to be of avail for out-of-sample forecasting. Well known model selection methods include the least absolute shrinkage and

[1]This chapter is based on Boskovic and Gross (2021)

selector operator (LASSO, (Tibshirani, 1996), Adaptive LASSO (Zou, 2006), Elastic Net (Zou and Hastie, 2005), Adaptive Elastic Net (Zou and Zhang, 2009), and other variants which we will reference later. They co-exist with step-wise selection algorithms (Hurvich and Tsai, 1990; Roecker, 1991; Derksen and Keselman, 1992).

All such methodologies are generally employed in a reduced-form manner, following a "let the data speak" philosophy. There is conventionally no role for theory to inform neither the relative importance of predictors nor the expected signs of causal relationships when such methods are used. If data were abundant and not inflicted with noise, this should be unproblematic. However, empirical analyses often operate with data of insufficient quality along some dimensions, including limited time series and/or cross-section observation coverage, and noise of different kinds.

Against this background, the aim of this paper is to promote the incorporation of theory-implied constraints on the signs of coefficients or linear combinations of them to thereby render existing model selection methods even more valuable. The value of doing so lies in (1) helping the methodologies find the true model (conditional on the assumptions implied by theory being correct), and (2) possibly helping enhance econometric efficiency. Both are relevant considerations especially when dealing with data of the kind hinted to above (noise, limited observations, etc). This is of particular importance for the process of financial system stress testing which saw an increase of its use and importance to policy makers following the Global Financial Crisis. Stress testing involves selecting the models that are used to establish a link between bank risk parameters with the macroeconomic and financial factors defined in a scenario, to use such econometric models to project the risk parameters' evolution conditional on the scenario into the future. Having a reliable model for such projections is of core importance for accurately forecasting and understanding the repercussions of potential adverse scenario. This applies to any economic forecasting procedure, in more general terms. While in the past, the models have been chosen at the researcher's discretion, there is a need for methods that will avoid the risk of "hand-picking" the model and mitigate the inherent model uncertainty. However, the challenge in front of model selection methods lies in the fact that the model has to conform to the economic theory, i.e. the relationship of the risk variable to its macroeconomic predictors has to make economic sense.[2] For instance, if the GDP falls, indicating a recession, we expect the probablilities of banks' defaut to increase. Having a model that claims otherwise would be useless for conditional scenario analysis. In our attempt to add new statistically and economically sound methods for model selection to the stress-testers toolkit, we augment the shrinkage based model selection methods to include the imposition of sign constraints, as we found no existing variants of these methods to be used for the purpose of financial stress testing.

The paper is structured as follows: We outline the econometric setting and the sign constraints methodology in Section 4.2, along with various relevant references to the literature. A series of Monte Carlo experiments is presented in Section 4.3 to show that sign constraints can enhance model identification and econometric efficiency. An empirical application in Section 4.4, involving data for nonfinancial

[2]Stress testers like the ECB and the IMF employ methods such as Bayesian Model Averaging (BMA) approach in combination with the imposition of sign constraints on prior equations. The equations that do not conform with the imposed constraints are excluded from the posterior model obtained by the BMA, making sure that the model used for scenario analysis conforms with economic theory.

firm default rates and a pool of macro-financial predictor variables from 16 countries, is used to show that the unconstrained model selection methods often result in models whose estimates are not conform with theory, and that the imposition of the sign constraints well serves its practical purpose.

4.2 Econometric Setting

4.2.1 Methods for Variable Selection and Regularization

Model selection methodologies involve a form of regularization, trading off variance and bias. The econometric structures of various model shrinkage methods are summarized in Table A.4.1. The methods can be upfront-categorized regarding (1) their adherence to the so-called Oracle property, and (2) whether they can handle the presence of correlated predictors. The schematic in Figure 1 depicts where the different methodologies are positioned along these two dimensions.

For a method to hold the Oracle property, two conditions should be satisfied: (1) It should be able to identify the correct subset model, and (2) consistency in coefficient estimation. According to (Fan and Li, 2001), a good procedure should possess these properties along with continuous shrinkage to be deemed optimal. In order to achieve the oracle property of the conventional LASSO methodology, Zou (2006) proposes Adaptive LASSO that modifies the penalty function introducing different weights w to the penalty term of each coefficient in order to avoid over-shrinking of large coefficients.

Table A.4.1: Overview of penalty regression methods for model selection

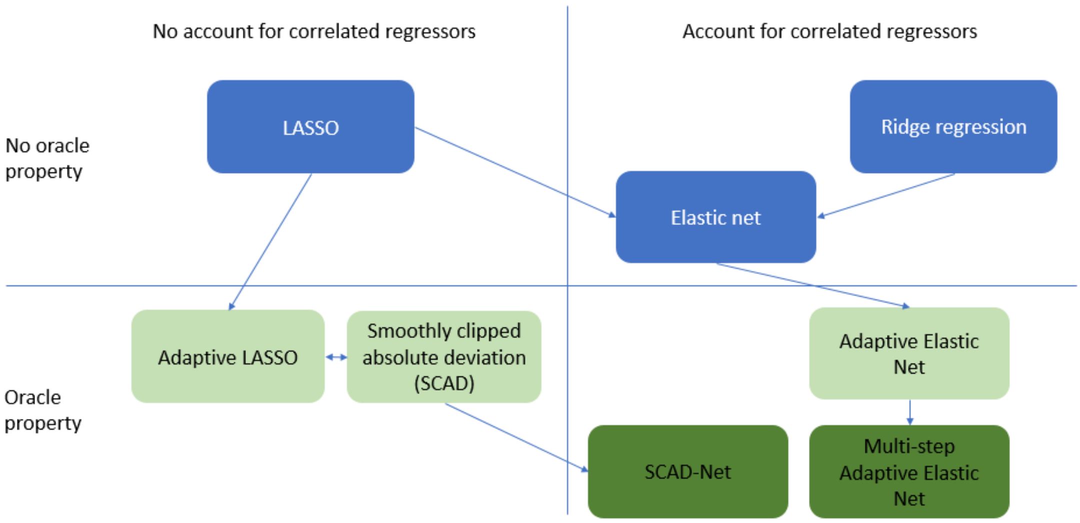
Method	**Main reference**	**General form**
Ridge regression	Hoerl (1962)	$\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} x_j \beta_j \right\Vert^2 + \lambda \sum_{j=1}^{p} {\beta_j}^2$
Non-negative garrote	Breiman (1995)	$\boldsymbol{\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} c_k x_j \beta_j \right\Vert^2}$ under constraints $\boldsymbol{c_k \geq 0, \sum_{j=1}^{p} c_k \leq s}$
LASSO	Tibshirani (1996)	$\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} x_j \beta_j \right\Vert^2 + \lambda \sum_{j=1}^{p} \lvert \beta_j \rvert$
Adaptive LASSO (A-LASSO)	Zou (2006)	$\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} x_j \beta_j \right\Vert^2 + \lambda \sum_{j=1}^{p} w_j \lvert \beta_j \rvert$
Elastic Net (ELNET)	Zou and Hastie (2005)	$\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} x_j \beta_j \right\Vert^2 + \lambda (\frac{1-\alpha}{2} \sum_{j=1}^{p} {\beta_j}^2 + \alpha \sum_{j=1}^{p} \lvert \beta_j \rvert)$
Adaptive ELNET (A-ELNET)	Zou and Zhang (2009)	$\hat{\beta} = \min_{\beta} \left\Vert y - \sum_{j=1}^{p} x_j \beta_j \right\Vert^2 + \lambda (\frac{1-\alpha}{2} \sum_{j=1}^{p} {\beta_j}^2 + \alpha \sum_{j=1}^{p} w_j \lvert \beta_j \rvert)$

Lasso and its follow-up variants aim to produce sparse and parsimonious models, in addition to compressing variance. Lasso is a shrinkage methodology that performs variable selection. It minimizes the sum of squared errors, with a bound on the sum of the absolute values of the coefficients. While Lasso uses L1 regularization term, and Ridge regression uses L2 regularization term, Elastic net is a methodological combination of the two that at the same time produces a parsimonious model and addresses some of the shortcomings of Lasso. Elastic net can account for correlated regressors and include them in the model in a grouped manner, while still performing a variable selection, that is, shrinking some of the coefficients to zero.

Since Lasso penalizes all coefficients in the same manner – resulting in over penalization of large coefficients – Lasso has been shown to not always be consistent, unless certain conditions are satisfied ((Meinshausen and Bühlmann, 2006). To address this issue, Fan and Li (2001) developed a concave penalty function called Smoothly clipped absolute deviation (SCAD), and proved that the model selected by this method has the so called oracle property, i.e. tends to identify the true variables as the sample size increases to infinity, with coefficients converging to true coefficients.

Lasso shrinks some of model coefficients to zero and thereby performs variable selection. It minimizes the sum of squared errors, with a bound on the sum of the absolute values of the coefficients. While Lasso uses an L1 regularization term, Ridge regression (Hoerl, 1959) uses an L2 regularization. Elastic net is a methodological combination of the two that at the same time produces a parsimonious model but, in addition to Lasso, accounts for correlated regressors. Since Lasso penalizes all coefficients in the same manner, resulting in over-penalization of large coefficients, it

Figure A.4.1: Categorization of model shrinkage and selection methodologies



Source: Authors

is proven to not always be consistent, unless certain conditions are satisfied (Meinshausen and Bühlmann, 2006). To address this issue, Fan and Li (2001) developed a concave penalty function for a method they call Smoothly Clipped Absolute Deviation (SCAD). They proved that this method has the Oracle property.

Zou (2006) proposes Adaptive Lasso as a solution to this challenge, proving the existence of its Oracle property. The Adaptive Lasso is a convex optimization problem with an L1 constraint. Therefore, it can be solved by the same efficient algorithm that is used for solving the Lasso (that is, the LARS algorithm, see Efron et al. 2004). Zou (2006) proves that adaptive Lasso is at least as competitive as methods with other concave penalties, while being computationally more attractive. Following the same principles, Ghosh (2007) proposes an adaptive version of elastic net, combining the advantages of elastic net over its predecessors in dealing with correlated regressors, then with an Oracle property. Xiao and Xu (2015) propose a multi-step adaptive elastic net, which, in addition to previously established properties of the method, reduces false positives in high-dimensional variable selection problems.

Several other extensions of the Lasso methodology were developed. For instance, Yuan and Lin (2006) proposed the group Lasso, to address the model selection when groups of regressors are jointly relevant and need to be selected into the models as a group. Wang and Leng (2008) propose an adaptive group Lasso that addresses the same issue, addressing the inconsistency of group Lasso. Tibshirani and Suo (2016) propose an order-constrained version of L1-regularized regression to address prediction problems involving time-lagged variables, and therefore being suitable for time series model selection.

We contemplate an extension for all such methods by adding linear inequality constraints to the coefficient sets of the model, to thereby weave in prior information into the model selection procedure. The following section summarizes how to go about this.

4.2.2 Vector-Sign Constrained Model Selection

The idea to impose constraints on the signs of sums of coefficients arises in particular in time series econometric applications, where different groups of predictor variables may reflect the contemporaneous and lagged inclusion of a given predictor. Considering such inclusion of predictors in contemporaneous and lagged form also implies that a methodology that performs well in the presence of correlated regressors is particularly warranted, since many macro-financial time series are serially correlated to a non-negligible extent. Hence, an elastic net methodology involving an L2 regularization is part of the set of methodologies upon which we build the vector-sign constraint mechanism. In terms of the Oracle property, we choose to include both the non-adaptive initial versions (without the Oracle property) and their adaptive counterparts (with the Oracle property). The reason for doing so is that we wish to see how the addition of prior knowledge on the signs of coefficients or coefficient vector sums may "help the Oracle property" or not.

The constraints that we impose on all four focus methods can generically be written as follows:

$$C\beta \leq d \tag{4.1}$$

Where β is, as above Kx1 vector of regression coefficients, C is a GxK constraints matrix which ought to have full rank (G counts the number of constraints imposed), and d is a Gx1 vector that completes the constraints.

We have identified five papers that relate to the imposition of linear equality or inequality constraints in the literature: James et al. (2019) develop what they call the Penalized and Constrained (PaC) algorithm which can be used to estimate Lasso estimation problems with linear equality and inequality constraints. The inequality constraints are just in an annex and with an emphasis on the algorithm for estimating such model structures. They consider an application high-dimensional website advertising data. Zhou and Lange (2013) propose a path-following algorithm for quadratic programming that replaces hard constraints by what are called exact penalties. Hu et al. (2015) derive the dual of the linear constrained generalized Lasso and propose a coordinate descent algorithm for calculating primal and dual solutions. They suggest that coordinate descent can be replaced with quadratic programing when its efficient and stable implementation is possible. Their simulation exercises pertain to the performance regarding the degree of freedom estimation and tuning parameter selection (via AIC vs. BIC). Gaines et al. (2018) employ three algorithms for estimating constrained Lasso: quadratic programming, an alternating direction method of multipliers, and their own solution path algorithm. They focus on the comparative computational efficiency of the three estimation methods, including with a view to runtime when larger scale applications are considered. Finally, Wu et al. (2021) propose an L1 penalized constrained least absolute deviation (LAD) method. The motivation for doing so is seen in cases where heavy-tailed errors or outliers are present, for the variance of the errors to become unbound, in which case constrained Lasso is no longer applicable.

This array of research has overall dealt with estimation algorithms and computational efficiency of constrained Lasso-type problem. The ability of the imposition of constraints to boost their predictive ability, including with a view to econometric efficiency, has not been addressed as far as we see. This is where we aim to contribute: By exploring the avail of sign constraints systematically for a range of methods, with a focus on the gain they may imply for enhancing the Oracle property for methods that do not initially carry it, for improving efficiency for those that do possess it, as well as by flanking our analytical work with an empirical application that is relevant in the field of bank stress testing.

4.3 Numerical Simulations

To explore the performance of the regular and the vector-sign constrained variants of of the four model selection methods, we run an array of simulations. We consider the following data generating process (DGP):

$$g_{i,t} = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon_{i,t} \tag{4.2}$$

where $\varepsilon_{i,t}$ is i.i.d. Gaussian disturbance with mean zero and variance Σ. To explore the performance of each method in presence of different levels of the cross-correlation among the regressors, we generate the coefficient correlation matrix using

Table A.4.2: Data generating process

Coefficients:	β_1-β_8 = (2 -0.7 0 0 -1.5 0.5 0 0)
Noise levels:	γ = (0.5, 1, 2)
Sample size:	n = (40, 120, 500)
Data correlation parameter:	σ = (0, 0.75)
Replication datasets:	D = 20000

the following equation:

$$corr(i,j) = \sigma^{|i-j|} \tag{4.3}$$

where i and j count the predictor variables contained in X. Table A.4.2 summarizes the parameterization of the DGP that we consider as a starting point for all simulations. Two cases are considered for the covariance structure of the predictors: zero covariance vs. strong covariance. Three cases are considered in terms of error variance and implied signal to noise ratios (high, medium and low): the error variances at 0.5, 1, and 2 let the implied signal to noise ratios amount to 29.7, 8.2, and 2.8, respectively.

For the sign constrained versions of the four methods, we impose the constraints on two sets of coefficients, defining C and d from equation 4.1 for individual constraints as in equation 4.4 and for joint coefficient constraints as under equation 4.5:

$$C^{indiv} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix} \tag{4.4}$$

$$C^{joint} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 \end{bmatrix} \tag{4.5}$$

From the set of six true models (one mean coefficient vector, two predictor correlation structures, three error variance settings), we simulate 20,000 artificial data sets for all predictors and the implied dependent variable, of sample size n=(40, 120, 500) for each of them. For all 20,000 data sets under all six settings, the first 75 percent of the sample are used for variable selection and estimation, while the remaining 25 percent of the observations per data set are considered as an out-of-sample portion based on which the predictive accuracy is assessed. For the in-sample variable selection and estimation, we employ a five-fold cross-validation methodology for obtaining the optimal shrinkage parameter λ. For the Elastic Net methods, we set the tuning parameter (alpha) to a value of 0.5, which implies an equal weight for the L1 and L2 penalty terms. In that way, we combine the feature selection capability of Lasso and the ability of ridge regressions to handle multicollinearity in the dataset. Predictive accuracy is judged with a view to (1) the percentage of correctly identified predictor sets, and (2) their root mean square errors (RMSEs).

Tables A.4.5 and A.4.6 show the percentage of correctly identified predictor sets over the 20,000 simulation rounds (median) for the samples with low and high correlation between regressors, respectively.

Imposing individual constraints on coefficients is found to perform better in terms of model identification than their unconstrained counterparts, showing that the imposition of constraints improves the Oracle property in the domain of correct identification of the model. This is especially true for adaptive Lasso, which improves the model identification by up to 33 percent in small samples with no correlation between regressors. This is not surprising, as it has been proven that adaptive Lasso has the Oracle property which the simple Lasso does not, and thus is superior in terms of its predictive performance and model identification. Despite the adaptive variants having the Oracle property, the addition of sign constraints still helps in small samples, and/or with notable noise.

Applying individual constraints increases the efficiency of selected methods in identifying the correct model even when correlation between regressors is high (Table A.4.6). In this setting, only in a very small sample with high noise there is no visible improvement. In line with its theoretical properties, elastic net methods perform the best in model selection when correlation between regressors is high. It is also notable that adaptive versions outperform non-adaptive versions, in particular in small samples with correlated regressors. Therefore, it is not surprising that adaptive-elastic net performs the best in model identification, as variables selection by adaptive elastic net somewhat combines that of elastic net and adaptive lasso (Ghosh, 2007).

In both settings, applying joint constraints does not improve the success rate in correct variable identification. However, although joint constraints methods do not outperform their unconstrained counterparts, they perform no worse. Their value-added lies in their importance in empirical applications, when econometric models require such grouping of coefficients, such as in financial stress testing, as it will be shown in the section dedicated to the empirical application.

Table A.4.7 shows the out-of-sample RMSE estimates resulting from all methodologies in a setting when there is no correlation between regressors. OLS model RMSEs are included as a benchmark here, where irrelevant regressors are included by design, which impinges on econometric efficiency, while being free of any source of potential bias.

For all methods under scrutiny, adding the individual sign constraints decreases the RMSE and therefore enhances prediction accuracy, that is, they help the Oracle property in its second dimension. This is most notable in case of aLasso whose RMSEs perform as well as or better than from OLS. The addition of joint constraints to selected methods only occasionally improves their performance in terms of their out-of-sample RMSEs. When considering no correlation of regressors, this is the case in small samples, combined with high noise. However, the improvement is not as substantial as it is with the individual constraints. In the sample with correlated regressors, the evidence is mixed: joint constraints lead to slight improvements in samples with moderate noise.

Although some methods come close to the OLS performance when we observe their RMSE performance, most methods will expectedly perform worse than the OLS and still imply some bias by their design. To show how the different features of these methods can be combined in a way to empirically make their best use, we provide a refitted OLS estimate based on the subset of variables chosen by each method – as is common practice by many practitioners in the field – to reduce the bias of those methods. The resulting RMSEs are reported in Tables A.4.9 and A.4.10 in the Appendix.

In conclusion, we show that imposing individual constraints on a set of model selection methods improves their Oracle property, meaning better predictive accuracy and correct model identification in small samples. The imposition of joint constraints does not necessarily do so, but even when they do not imply an improvement, they do not cause any deterioration in predictive performance either. Their most notable value remains to be seen in empirical applications, as incorporating prior knowledge in model identification should help align the a model's structure with theory.

4.4 Empirical Exercise

To examine the performance of the sign constrained (a)Lasso and (a)Elastic Net, we employ them for an empirical application in the field of financial stress testing. Financial sector stress testing is an important tool for assessing the resilience of the financial system and for gauging risks arising at system-wide level from a macroprudential perspective. The financial crisis and its aftermath led to a greater use of stress tests, including with a view to informing the timing and calibration of macroprudential policies. Stress testing involves selecting the models that are used to establish a link between bank risk parameters with the macro and financial factors defined in a scenario, to use such econometric models to project the risk parameters' evolution conditional on the scenario into the future. Useful entry points to stress test methodologies used at major central banks include, for example, (Dees et al., 2017).

The process of stress testing involves selecting the models that are used to establish a link between risk parameters with the macro and financial factors defined in a scenario, to thereby project the evolution of the market risk conditional on a scenario. The future paths of these variables are embedded in the scenarios used to conduct a forward-looking simulation of the evolution of the variables measuring systemic risk in the financial system. Having a reliable model selection methodology to disseminate model uncertainty inherent in so-called "hand-picked models" – those subject to the arbitration of the researcher – is of great importance in financial stress testing and economic forecasting in general. In addition, having a theoretically sound relationship between predicted variable and its regressors is crucial for meaningful predictions. For instance, economic intuition suggests that the increase in risk spread would potentially lead to higher probabilities of default, and having a positive sign on the Long-run multipliers (LRM) of risk spread is therefore of paramount importance. LRMs can be defined as follows:

Since for the application that follows we operate in a time series context, we define the notion of a long-run multiplier (LRM) for predictor X^k explicitly, on which we will impose the sign constraints:

$$\sum_{l=0}^{\infty} \sigma E(Y_{t+l}/\sigma X_t^k) = \frac{\hat{\beta}_0^k + ... + \hat{\beta}_q^k}{1 - \gamma_1 - ... - \gamma_p} \equiv \Theta^k \tag{4.6}$$

Table A.4.3: List of variables

Acronym	**Full variable name**	**LRM sign**
RGRP	Real GDP Growth	-
ITR	Real Investment Growth	-
CAPUTIL	Capacity Utilization	-
URX	Unemployment Rate (change)	+
CREDIT	Credit Growth	-
TS	Term Spread	+
RS	Risk Spread	+
CPI	Consumer price index growth, seasonally adjusted	-
EER	Effective exchange rate growth	+
OIL	Oil price	+

The dependent variable that we consider is a probability of default (PD) for non-financial listed corporates, sourced from Moody's KMV, with a quarterly frequency spanning the 2002Q1-2019Q4 period and comprising 16 countries for which the PDs are aggregated using firm assets as weights: Austria, Belgium, Czech Republic, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, Great Britain, and the United States. Models for PDs, next to a loss given default (LGD) component (see Dees et al. (2017), Chapter 4) as the second element to complete a credit risk assessment, play an important role in the overall stress test model suites, because loan losses constitute a major component of banks' profit and loss flows, next to interest income and expenses. It is, therefore, important that the credit risk models are developed in a robust manner, to ensure that they provide precise estimates for scenario-conditional PD paths.

Table A.4.3 lists the ten potential predictor variables that we consider, along with the LRM sign constraints that will be imposed.

We consider the time contemporaneous and lagged inclusion of these 10 variables. The empirical environment represents a case of non-negligible correlation among the potential predictors, including through the allowance for lagged terms for variables that are relatively persistent, such as price inflation and capacity utilization. To address the presence of such correlations, we set alpha, the elastic net parameter, to 0.5. Two autoregressive lags of the dependent variables are considered as well. They are included in the set of potential predictors, resulting in a total of 2x10+2=22 effective right hand-side variables, not counting the intercept. We use 5-fold cross validation to determine the optimal shrinkage parameter for each method.

Regarding the LRM sign constraints (A.4.3): Stronger GDP growth, real investment, capacity utilization and credit growth shall all come along with lower PDs. The opposite is true for the unemployment rate. Term and risk spreads gradually fall during booms and widen during ensuing recessions, hence implying the positive sign we impose. Regarding consumer price inflation, the relationship to PDs might be more ambiguous at times, as it depends on the nature of past recessions, which can be dominated by either a slump in demand or supply. Most historic recessions are dominated by dropping demand, making price inflation fall, and implying our preference for imposing a negative sign constraint, in line with GDP growth, and thereby implicitly having an assumed positive Phillips curve slope in the back of our minds as well. As all the countries included in the sample are net oil importers, they will all be negatively affected by an increase in oil price, thus raising firms' PDs. The sign of the effective exchange rate growth variable will depend on whether the country is net importer or net exporter, which can be time varying. When a country is a net importer, exchange rate appreciation will cause their exports to be more expensive, dampening a part of external demand and leading to higher PDs, while the net importers benefit from appreciation through stronger purchasing power abroad which implies lower PDs. We assign the positive constraint on exchange rate growth, but we prepare the data in such way to flip their sign in periods when the countries' net exports were negative, making a de facto negative constraint for these cases.

Figure A.4.6 shows the model structure and LRM estimates resulting from the double constrained adaptive elastic net for all countries. The coefficients were constrained to have the economically correct LRM sign. We can observe a notable heterogeneity in the LRM slopes across countries.

When unconstrained, these variables would often enter the model equation with incorrect signs and therefore be less useful for forward looking scenario analyses. To judge the materiality of such issue, we examine the coefficients' signs in models selected by the unconstrained (a)Lasso and (a)Elastic Net variants. We report the portion of variables with incorrect signs in the cross-section of countries in Table A.4.4. The average across all variables and the four methods (excluding OLS) amounts to 42 percent. Except regarding the risk spread, this percentage is notable for all variables and all methods. Some variables, such as real GDP growth, would enter the models with an incorrect sign up to 75 percent of the times (with aLasso). Tables in the Appendix report the detailed country-specific results underlying the percentages in Table A.4.4.

The sizable occurrence of theory non-conform signs is problematic and limiting the use of unconstrained model selection methods for economic forecasting, including stress testing (conditional forecasting). Models that feature counterintitive relationship between predictors and the dependent variable have little to no use in such procedures. The imposition of sign constraints to model selection methods addresses

Table A.4.4: Percentage of times a variable is included in an unconstrained model with a wrong sign

	OLS	LASSO	aLASSO	ENET	aENET
RGRP	68.8%	37.5%	75.0%	50.0%	75.0%
ITR	18.8%	12.5%	37.5%	31.3%	37.5%
URX	56.3%	18.8%	31.3%	6.3%	18.8%
CAPUTIL	37.5%	50.0%	37.5%	50.0%	50.0%
CREDIT	62.5%	81.3%	68.8%	43.8%	56.3%
TS	50.0%	62.5%	62.5%	68.8%	56.3%
RS	0.0%	0.0%	0.0%	0.0%	6.3%
CPI	56.3%	18.8%	68.8%	31.3%	68.8%
EER	68.8%	62.5%	68.8%	50.0%	62.5%
OIL	18.8%	18.8%	12.5%	18.8%	31.3%

this challenge, by allowing for incorporating prior theoretical and expert-based economic reasoning. Although, based on the numerical simulation, we don't expect efficiency improvements when using the joint constraints, their practical application is of crucial importance in scenarios where there is a need to pose constraints on a sum of two or more variables, as it is the case with the long term multipliers presented in our empirical excercise. In addition, they are easily adapted to a range financial or macroeconomic projection exercises. Importantly, model and estimation uncertainty are often aggravated for stress testers, when operating in weak data environments (short time series, noisy/imperfect data, etc.). Hence, the imposition of prior assumptions on the sign of relationships should be beneficial from that perspective.

4.5 Conclusion

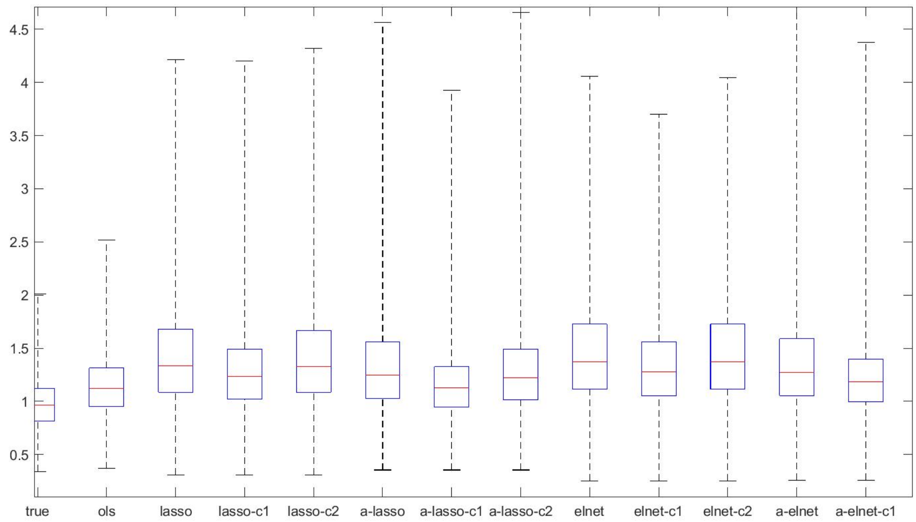
The objective of this paper was to promote the idea of imposing sign constraints on individual model coefficients or linear combinations thereof when employing otherwise conventional (a)Lasso and (a)Elastic-Net model selection methodologies. The purpose of doing so lies in enhancing the model identification and predictive accuracy in small data samples, which are possibly inflicted with noise.

Our Monte Carlo simulations suggest that this is a valuable strategy: the addition of sign constraints "helps the Oracle property", that is, the ability to identify the true model, for those methods that do not initially carry it, such as Lasso, in finite data samples. For methods that possess it already (the adaptive variants), the constraints help increase efficiency in small samples, conditional in all cases on the constraints being correct.

We examine the use of inequality constraints on the signs of both individual coefficients and joint coefficients. The latter can be useful in empirical applications, which we illustrate with a time series application where the joint set pertains to the long-run multipliers of the respective predictor variables. The empirical analysis entailed the use of probability of default metrics, which are one central element in larger scale bank stress test model suites, and which in practical applications is often challenged by short, noisy data. Having model selection methods that allow pre-informing the structure and estimates of the equations shall therefore be instrumental to obtain as robust models as feasible.

4.6 Appendix

Figure A.4.2: Distributions of RMSEs in small sample, no correlation



Note: This table shows the distribution of out-of-sample RMSEs of each method over the 20,000 simulation rounds (median) with the following characteristics: N=40, noise = 1, σ = 0.

Table A.4.5: Percentage of correctly selected predictor sets ($\sigma = 0$)

Method	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=120, Î´=0.5	n=120, Î´=1	n=120, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
LASSO	0.94	0.60	0.29	1.00	0.95	0.58	1.00	1.00	0.97
LASSO-C*	0.96	0.73	0.41	1.00	0.98	0.76	1.00	1.00	0.99
LASSO-C**	0.94	0.60	0.29	1.00	0.95	0.59	1.00	1.00	0.97
aLASSO	0.89	0.58	0.37	0.96	0.89	0.59	0.96	0.96	0.92
aLASSO-C*	0.97	0.77	0.47	1.00	0.98	0.77	1.00	1.00	0.99
aLASSO-C**	0.89	0.58	0.35	0.96	0.89	0.59	0.95	0.96	0.91
enet	0.95	0.75	0.44	1.00	0.97	0.74	1.00	1.00	0.98
enet-C*	0.97	0.82	0.55	1.00	0.98	0.84	0.99	1.00	0.99
enet-C**	0.95	0.75	0.44	1.00	0.96	0.75	1.00	1.00	0.98
aEnet	0.93	0.74	0.47	0.99	0.95	0.76	1.00	0.99	0.96
aEnet-C*	0.97	0.82	0.53	1.00	0.98	0.83	1.00	1.00	0.99
aEnet-C**	0.93	0.74	0.45	0.99	0.94	0.75	0.99	0.99	0.96

Note: This table shows the percentage of correctly selected predictor sets per each method, different noise levels and sample sizes when there is no correlation between regressors. C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Table A.4.6: Percentage of correctly selected predictor sets ($\sigma = 0.75$)

Method	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=120, Î´=0.5	n=120, Î´=1	n=120, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
LASSO	0.70	0.31	0.18	0.99	0.74	0.32	1.00	0.99	0.79
LASSO-C*	0.76	0.39	0.18	0.99	0.80	0.40	1.00	1.00	0.84
LASSO-C**	0.70	0.31	0.17	0.99	0.75	0.32	1.00	1.00	0.80
aLASSO	0.70	0.41	0.27	0.96	0.73	0.43	0.97	0.97	0.76
aLASSO-C*	0.80	0.48	0.23	0.99	0.81	0.48	1.00	1.00	0.84
aLASSO-C**	0.70	0.41	0.25	0.96	0.73	0.42	0.97	0.96	0.76
enet	0.74	0.45	0.28	0.99	0.78	0.44	1.00	1.00	0.83
enet-C*	0.80	0.44	0.22	0.99	0.84	0.46	1.00	1.00	0.89
enet-C**	0.74	0.45	0.27	0.99	0.78	0.46	1.00	1.00	0.83
aEnet	0.81	0.49	0.31	0.98	0.82	0.50	0.99	0.98	0.85
aEnet-C*	0.86	0.53	0.25	1.00	0.88	0.52	1.00	1.00	0.90
aEnet-C**	0.82	0.50	0.29	0.98	0.83	0.50	0.99	0.98	0.86

Note: This table shows the percentage of correctly selected predictor sets per each method, different noise levels and sample sizes when there is substantial correlation between regressors. C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Table A.4.7: Median RMSEs per each method ($\sigma = 0$)

Method	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=120, Î´=0.5	n=120, Î´=1	n=120, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
OLS	0.57	1.14	2.28	0.52	1.04	2.08	0.50	1.01	2.02
LASSO	0.76	1.43	2.54	0.75	1.16	2.28	0.75	1.15	2.09
LASSO-C*	0.73***	1.29***	2.37***	0.74***	1.14***	2.16***	0.75***	1.14***	2.07***
LASSO-C**	0.76	1.42	2.53	0.75	1.16	2.26***	0.75	1.15	2.09
aLASSO	0.85	1.42	2.47	0.90	1.33	2.29	0.78	1.32	2.24
aLASSO-C*	0.57***	1.16***	2.28***	0.52***	1.04***	2.09***	0.50***	1.01***	2.02***
aLASSO-C**	0.79	1.35***	2.44***	0.88	1.29***	2.25***	0.79	1.32	2.23
enet	1.00	1.57	2.68	1.01	1.40	2.41	1.24	1.50	2.29
enet-C*	0.97***	1.48***	2.49***	0.98***	1.37***	2.30***	1.18***	1.46***	2.26***
enet-C**	1.00	1.56	2.68	1.01	1.40	2.39***	1.24	1.50	2.29
aEnet	0.99	1.55	2.65	0.94	1.37	2.38	0.92	1.28	2.22
aEnet-C*	0.86***	1.34***	2.47***	0.81***	1.23***	2.22***	0.79***	1.18***	2.13***
aEnet-C**	0.97***	1.49***	2.62***	0.94	1.35	2.36***	0.92	1.28	2.22

Note: This table shows the median RMSEs per each method, different noise levels and sample sizes when there is no correlation between regressors. * the distribution of RMSEs significantly differs from its unconstrained counterpart (at 5% significance level) C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Table A.4.8: Median RMSEs per each method ($\sigma = 0.75$)

Method	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=120, Î´=0.5	n=120, Î´=1	n=120, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
OLS	0.57	1.14	2.28	0.52	1.04	2.08	0.50	1.01	2.02
LASSO	0.68	1.29	2.32	0.57	1.11	2.18	0.57	1.04	2.06
LASSO-C*	0.64***	1.23***	2.25***	0.56	1.08***	2.13***	0.57	1.03	2.03***
LASSO-C**	0.67	1.28	2.31	0.57	1.10	2.17***	0.57	1.04	2.05
aLASSO	0.74	1.32	2.33	0.70	1.19	2.21	0.69	1.16	2.12
aLASSO-C*	0.60***	1.18***	2.25***	0.54***	1.06***	2.11***	0.52***	1.02***	2.03***
aLASSO-C**	0.69***	1.26***	2.32	0.69	1.16***	2.18***	0.70	1.16***	2.11***
enet	0.83	1.38	2.42	0.73	1.22	2.27	0.69	1.13	2.12
enet-C*	0.83	1.34***	2.35***	0.74	1.20***	2.21***	0.69	1.13	2.11***
enet-C**	0.83	1.37	2.42	0.73	1.21	2.25***	0.69	1.13	2.12
aEnet	0.84	1.46	2.43	0.73	1.26	2.30	0.70	1.15	2.15
aEnet-C*	0.73***	1.32***	2.37***	0.65***	1.15***	2.20***	0.63***	1.09***	2.07***
aEnet-C**	0.81***	1.41***	2.42	0.73	1.24***	2.27***	0.70	1.15	2.14***

Note: This table shows the median RMSEs per each method, different noise levels and sample sizes when there is substential correlation between regressors. * the distribution of RMSEs significantly differs from its unconstrained counterpart (at 5% significance level) C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Table A.4.9: Median RMSEs for models reestimated by the OLS (no correlation)

	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=150, Î´=0.5	n=150, Î´=1	n=150, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
OLS	0.57	1.14	2.28	0.51	1.03	2.06	0.50	1.01	2.01
Lasso	0.55	1.15	2.26	0.51	1.02	2.07	0.50	1.00	2.01
Lasso-C*	0.54	1.13	2.27	0.51	1.02	2.06	0.50	1.00	2.01
Lasso -C**	0.55	1.15	2.26	0.51	1.02	2.07	0.50	1.00	2.01
aLasso	0.56	1.14	2.22	0.51	1.03	2.07	0.50	1.01	2.02
aLasso-C*	0.55	1.13	2.27	0.51	1.02	2.06	0.50	1.01	2.01
aLasso-C**	0.56	1.14	2.23	0.51	1.03	2.07	0.50	1.01	2.02
ElNet	0.55	1.14	2.25	0.51	1.02	2.07	0.50	1.00	2.01
ElNet-C*	0.55	1.13	2.26	0.51	1.02	2.06	0.50	1.00	2.01
ElNet-C**	0.55	1.14	2.26	0.51	1.02	2.07	0.50	1.00	2.01
aElNet	0.56	1.13	2.23	0.51	1.03	2.06	0.50	1.01	2.02
aElNet-C*	0.55	1.13	2.27	0.51	1.02	2.06	0.50	1.01	2.01
aElNet-C**	0.56	1.13	2.25	0.51	1.03	2.06	0.50	1.01	2.02

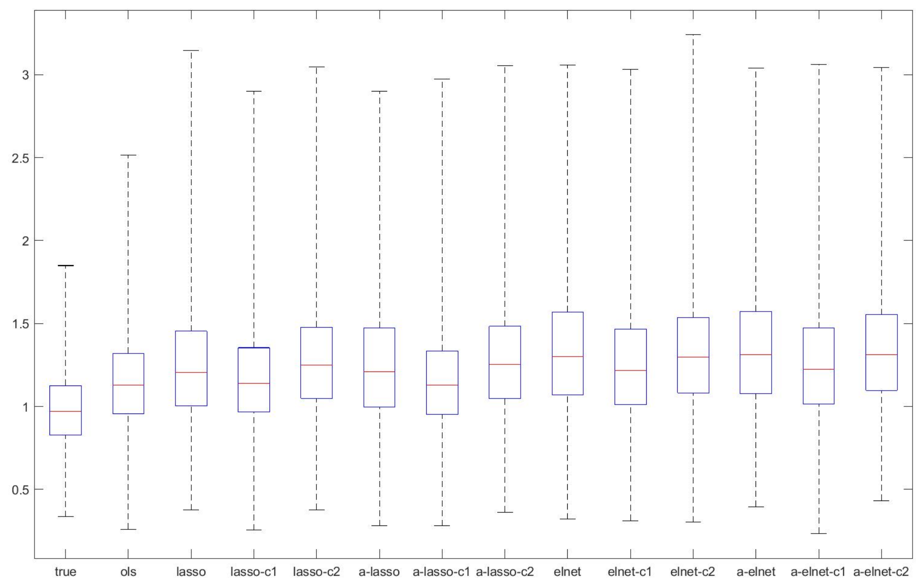
Note: This table shows the median RMSEs of models chosen by each method and reestimated by the OLS, different noise levels and sample sizes when there is no correlation between regressors. * the distribution of RMSEs significantly differs from its unconstrained counterpart (at 5% significance level) C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Table A.4.10: Median RMSEs for models reestimated by the OLS (high correlation)

	n=40, Î´=0.5	n=40, Î´=1	n=40, Î´=2	n=150, Î´=0.5	n=150, Î´=1	n=150, Î´=2	n=500, Î´=0.5	n=500, Î´=1	n=500, Î´=2
OLS	0.56	1.13	2.24	0.51	1.03	2.06	0.50	1.01	2.01
Lasso	0.59	1.15	2.17	0.51	1.04	2.07	0.50	1.01	2.02
Lasso-C*	0.58	1.14	2.21	0.51	1.03	2.07	0.50	1.01	2.02
Lasso-C**	0.57	1.17	2.22	0.51	1.03	2.07	0.50	1.01	2.02
aLasso	0.57	1.12	2.21	0.51	1.03	2.06	0.50	1.01	2.02
aLasso-C*	0.57	1.14	2.22	0.51	1.03	2.06	0.50	1.01	2.02
aLasso-C**	0.57	1.16	2.24	0.52	1.03	2.07	0.51	1.01	2.02
ElNet	0.58	1.15	2.16	0.51	1.04	2.07	0.50	1.01	2.02
ElNet-C*	0.58	1.14	2.21	0.51	1.03	2.07	0.50	1.01	2.02
ElNet-C**	0.57	1.17	2.22	0.52	1.03	2.07	0.50	1.01	2.02
aElNet	0.56	1.12	2.20	0.51	1.03	2.06	0.50	1.01	2.02
aElNet-C*	0.56	1.14	2.21	0.51	1.03	2.06	0.50	1.01	2.01
aElNet-C**	0.57	1.16	2.23	0.52	1.03	2.07	0.51	1.01	2.02

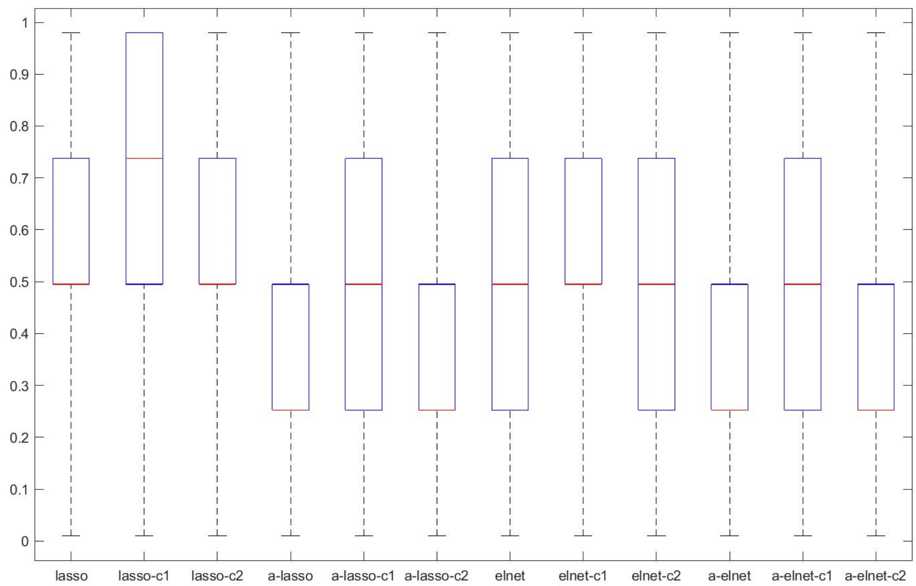
Note: This table shows the median RMSEs of models chosen by each method and reestimated by the OLS, different noise levels and sample sizes when there is substential correlation between regressors. * the distribution of RMSEs significantly differs from its unconstrained counterpart (at 5% significance level) C*- constraints applied to individual coefficients, C** - constraints applied to groups of coefficients

Figure A.4.3: Distributions of RMSEs in small sample, high correlation



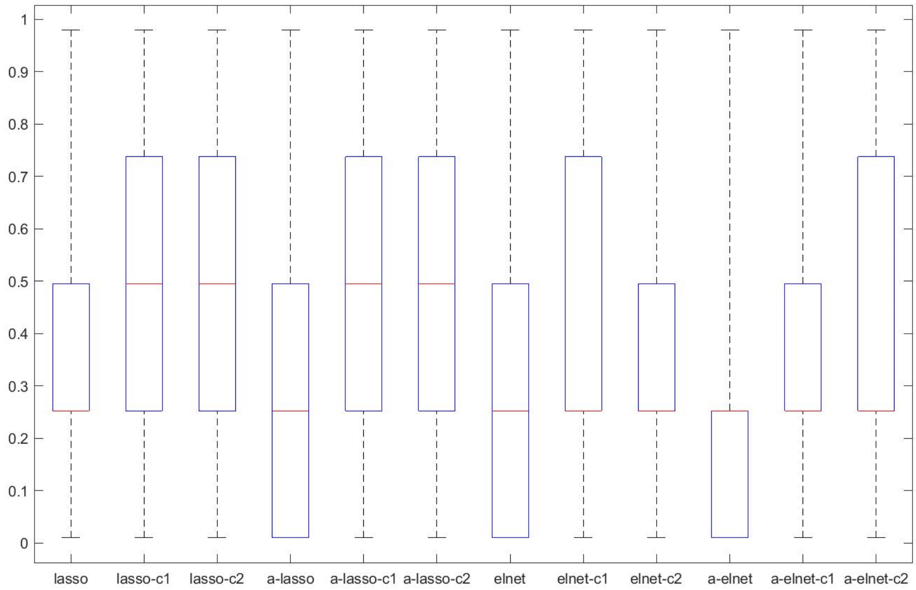
Note: This table shows the distribution of out-of-sample RMSEs of each method over the 20,000 simulation rounds (median) with the following characteristics: N=40, noise = 1, σ = 0.75.

Figure A.4.4: Shrinkage parameter distributions in small sample, no correlation



Note: This table shows the distribution of shrinkage parameters chosen by each method over the 20,000 simulation rounds (median) with the following characteristics: N=40, noise = 1, σ = 0.

Figure A.4.5: Shrinkage parameter distributions in small sample, high correlation



Note: This table shows the distribution of shrinkage parameters chosen by each method over the 20,000 simulation rounds (median) with the following characteristics: N=40, noise = 1, σ = 0.75.

Figure A.4.6: Coefficients chosen by double-constrained adaptive elastic net

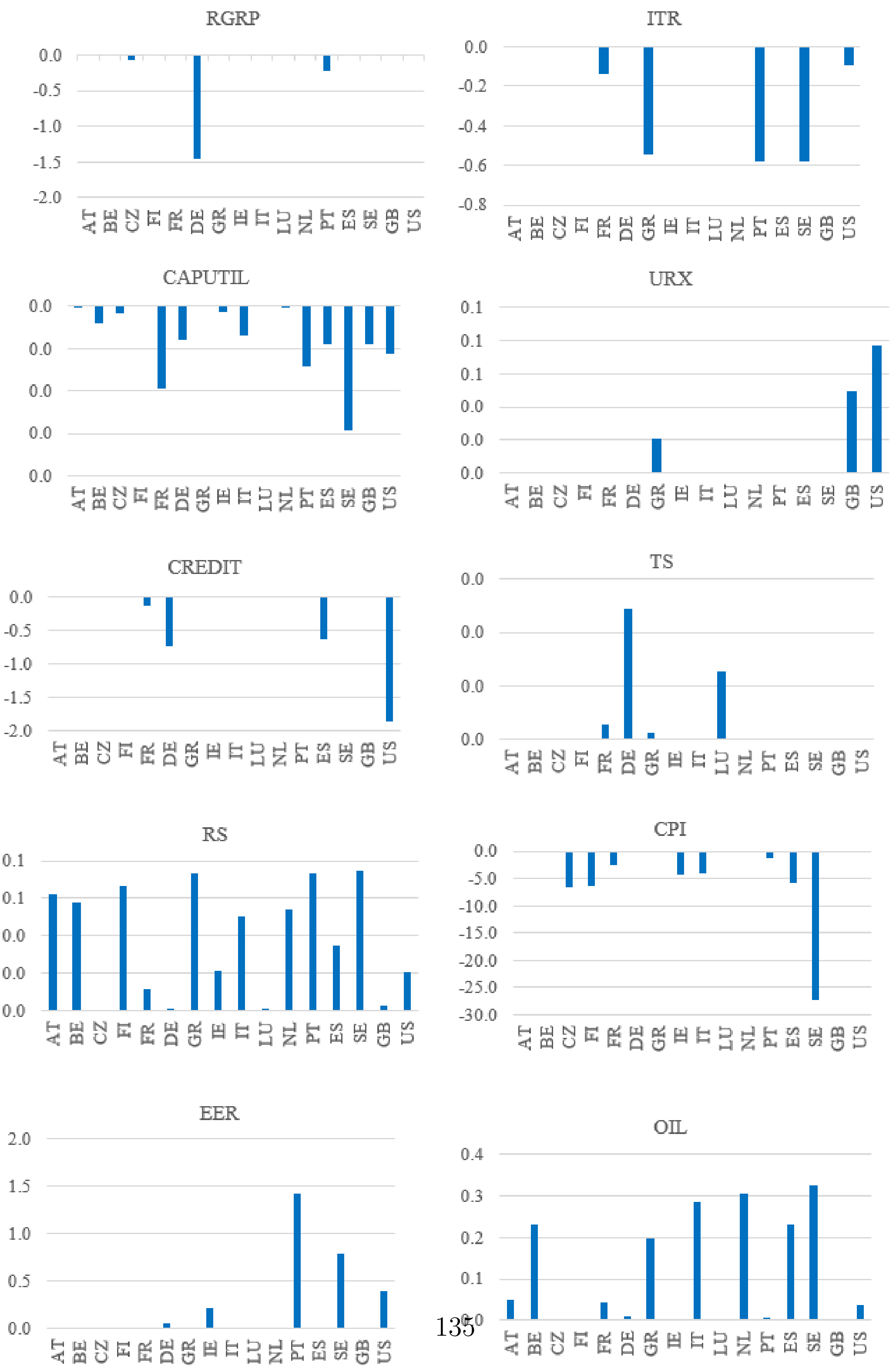


Table A.4.11: Inclusion frequency of the variables with the wrong LRM (OLS)

Country	RGRP	ITR	CAPUTIL	URX	CREDIT	TS	RS	CPI	EER	OIL	wrong sign
AT	1	0	1	0	1	1	0	0	1	0	50%
BE	1	0	1	0	1	1	0	0	1	0	50%
CZ	1	0	0	1	1	1	0	1	1	0	60%
FI	0	0	1	1	1	1	0	0	1	0	50%
FR	0	1	1	1	1	0	0	0	0	1	50%
DE	0	0	1	1	0	0	0	0	1	0	30%
GR	1	0	1	0	0	0	0	1	0	1	40%
IE	1	0	1	0	1	0	0	0	0	1	40%
IT	1	0	0	0	0	1	0	1	1	0	40%
LU	0	0	1	0	1	0	0	1	1	0	40%
NL	0	1	0	0	1	1	0	1	1	0	50%
PT	1	0	0	0	1	1	0	1	1	0	50%
ES	1	0	0	1	0	0	0	1	0	0	30%
SE	1	0	0	1	1	0	0	1	1	0	50%
GB	1	1	0	0	0	1	0	1	0	0	40%
US	1	0	1	0	0	0	0	0	1	0	30%

Note: This table shows how often is a variable chosen by OLS into the model with the wrong long-run multiplier sign in the empirical simulation.

Table A.4.12: Inclusion frequency of the variables with the wrong LRM (LASSO)

Country	RGRP	ITR	CAPUTIL	URX	CREDIT	TS	RS	CPI	EER	OIL	wrong sign
AT	1	0	1	0	1	1	0	0	1	0	50%
BE	1	0	1	0	1	1	0	0	1	0	50%
CZ	1	0	0	1	1	1	0	1	1	0	60%
FI	0	0	0	1	1	1	0	0	1	0	40%
FR	0	0	0	1	1	0	0	0	0	1	30%
DE	0	0	0	1	1	1	0	0	0	0	30%
GR	0	1	0	0	1	1	0	0	0	0	30%
IE	1	0	0	0	1	0	0	0	1	1	40%
IT	1	0	0	1	0	1	0	1	1	0	50%
LU	0	0	1	1	1	1	0	0	0	0	40%
NL	0	1	0	0	1	1	0	0	1	0	40%
PT	1	0	0	0	1	0	0	1	0	1	40%
ES	0	0	0	1	1	1	0	0	1	0	40%
SE	0	0	0	1	1	0	0	0	1	0	30%
GB	0	0	0	0	1	1	0	0	0	0	20%
US	0	0	0	0	0	0	0	0	1	0	10%

Note: This table shows how often is a variable chosen by LASSO into the model with the wrong long-run multiplier sign in the empirical simulation.

Table A.4.13: Inclusion frequency of the variables with the wrong LRM (aLASSO)

Country	RGRP	ITR	CAPUTIL	URX	CREDIT	TS	RS	CPI	EER	OIL	wrong sign
AT	1	0	1	0	1	1	0	0	1	0	50%
BE	0	0	0	1	1	1	0	0	1	0	40%
CZ	1	0	0	1	1	1	0	1	1	0	60%
FI	0	0	0	1	1	1	0	1	1	0	50%
FR	1	1	1	0	1	1	0	1	0	0	60%
DE	0	1	0	1	0	1	0	0	1	0	40%
GR	1	0	1	0	0	0	0	1	0	1	40%
IE	1	0	1	0	1	0	0	0	0	1	40%
IT	1	0	0	0	1	0	0	1	1	0	40%
LU	1	0	1	0	1	0	0	1	1	0	50%
NL	1	1	0	0	1	1	0	1	1	0	60%
PT	1	0	0	0	1	1	0	1	1	0	50%
ES	1	1	0	1	0	1	0	1	1	0	60%
SE	1	0	0	1	1	0	0	1	0	0	40%
GB	1	1	0	0	0	1	0	1	0	0	40%
US	0	1	0	0	0	0	0	0	1	0	20%

Note: This table shows how often is a variable chosen by Adaptive LASSO into the model with the wrong long-run multiplier sign in the empirical simulation.

Table A.4.14: Inclusion frequency of the variables with the wrong LRM (eNET)

Country	RGRP	ITR	CAPUTIL	URX	CREDIT	TS	RS	CPI	EER	OIL	wrong sign
AT	1	0	0	0	1	1	0	0	1	0	40%
BE	1	0	0	1	1	1	0	1	1	0	60%
CZ	0	1	0	1	0	0	0	0	0	0	20%
FI	1	1	0	0	1	0	0	1	1	1	60%
FR	0	0	0	1	1	1	0	0	0	0	30%
DE	1	1	0	1	0	1	0	1	0	1	60%
GR	1	0	0	0	0	0	0	1	0	0	20%
IE	1	0	0	1	1	0	0	0	1	1	50%
IT	0	0	0	0	0	1	0	0	1	0	20%
LU	0	0	1	1	1	1	0	0	0	0	40%
NL	0	1	0	0	0	1	0	0	0	0	20%
PT	1	0	0	0	0	1	0	0	1	0	30%
ES	1	0	0	1	0	1	0	1	1	0	50%
SE	0	1	0	1	0	1	0	0	0	0	30%
GB	0	0	0	0	1	1	0	0	0	0	20%
US	0	0	0	0	0	0	0	0	1	0	10%

Note: This table shows how often is a variable chosen by Elastic Net into the model with the wrong long-run multiplier sign in the empirical simulation.

Table A.4.15: Inclusion frequency of the variables with the wrong LRM (aeNET)

Country	RGRP	ITR	CAPUTIL	URX	CREDIT	TS	RS	CPI	EER	OIL	wrong sign
AT	1	0	1	0	1	1	0	0	1	0	50%
BE	1	0	0	1	1	1	0	1	1	0	60%
CZ	0	1	0	0	0	0	0	1	1	1	40%
FI	1	1	0	1	1	1	0	1	0	0	60%
FR	0	1	0	1	1	0	0	0	0	1	40%
DE	1	0	0	1	0	1	0	1	1	1	60%
GR	1	0	0	0	0	0	0	1	0	0	20%
IE	1	0	1	0	1	0	0	0	0	1	40%
IT	1	0	0	0	0	0	0	1	1	0	30%
LU	0	0	1	1	1	1	0	1	0	0	50%
NL	1	1	0	0	1	1	0	1	1	0	60%
PT	1	0	0	0	1	1	0	1	1	0	50%
ES	1	0	0	1	0	1	0	1	1	0	50%
SE	1	1	0	1	0	1	0	0	1	0	50%
GB	1	0	0	1	1	0	1	1	0	1	60%
US	0	1	0	0	0	0	0	0	1	0	20%

Note: This table shows how often is a variable chosen by adaptive Elastic Net into the model with the wrong long-run multiplier sign in the empirical simulation.

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