



Essays in International Macroeconomics

Alejandro Viccondoa

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Abstract

This thesis studies the effects of external shocks on emerging economies and proposes a novel methodology to assess the spillovers from financial markets to the real economy.

The first chapter analyzes how anticipated and unanticipated fluctuations in the U.S. interest rate are transmitted to emerging economies. Exploiting Fed Funds future contracts, I propose a novel way to identify shocks to the U.S. interest rate. An anticipated (unanticipated) 25 basis points contractionary U.S. interest rate shock induces a fall of 0.5 percent in GDP of emerging economies one quarter before (after) the shock materializes. The observed dynamics are consistent with the predictions of a small open economy model augmented with a banking sector. Despite the change in relative prices, output significantly falls because banks face restricted access to international financial markets and, thus, tighten their credit supply.

The second chapter assesses the relevance of terms of trade fluctuations to explain emerging economies business cycles. Using a sample of Latin American countries, news-augmented Commodity-TOT (CTOT) shocks are identified by maximizing the forecast error variance share of the CTOT series at a finite future horizon. The combination of news and surprise CTOT shocks explains on average half of output fluctuations and anticipated shocks account for 53 percent of CTOT shocks.

The third chapter proposes a novel methodology, called Bridge Proxy-SVAR, to study the relationship between time series sampled at different frequencies. The methodology comprises three steps: (I) identify the structural shocks of interest in high frequency systems; (II) aggregate the series of high frequency shocks at the lower frequency; (III) use the aggregated series of shocks as a proxy for the corresponding structural shock in lower frequency VARs. The Bridge Proxy-SVAR generalizes the applicability of the Proxy-SVAR and significantly mitigates temporal aggregation biases.

The fourth chapter provides novel evidence on the large macroeconomic spillovers from changes in the liquidity of sovereign bonds by employing the Bridge Proxy-SVAR. Liquidity shocks, orthogonal to changes in default risk, induce strong recessionary effects in Italy.

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Chapter 1

Monetary News, U.S. Interest Rate and Business Cycles in Emerging Economies

1.1 Introduction

Over the last decades most emerging economies have increasingly opened their borders to financial flows. This integration has improved their access to international financial markets and substantially increased their interdependencies with developed economies. In this context, movements in the international interest rate have been identified as an important source of business cycle fluctuations in emerging economies. Fluctuations in the international interest rate may affect borrowing conditions, commodity prices, exchange rates, flows of capital, and the macroeconomic conditions of emerging economies. Although this topic has been widely studied, there is no consensus on the macroeconomic effects of variations in the U.S. interest rate on these economies.¹ Understanding the transmission of U.S. interest rate shocks is crucial not only for explaining business cycle fluctuations in emerging economies but also for designing monetary and macroprudential policies.

A common feature of previous empirical works is that they abstract from potential anticipation effects. However, many movements in the U.S. interest rate are anticipated by the market before they occur. A potential source of monetary anticipation is the practice of “forward guidance” through which the Central Bank informs the future course of monetary policy. Moreover, the Fed Funds Future contracts provide a market-based unbiased expectations indicator of interest rate’s evolution ([Owens and Webb \(2001\)](#); [Hamilton \(2009\)](#)). Capital flows, financial markets, and exchange rates may react to an expected movement before any change in the U.S. interest rate. [Hansen and Sargent \(1991\)](#) demonstrate that, in the case of anticipation, a Vector Autoregressive Model (VAR) with insufficient information (i.e. without considering agents’ expectations) fails to capture the dynamics of the variables. This fact may explain the lack of consensus from previous works about the effects of U.S. monetary policy shocks on emerging economies.

This paper identifies anticipated and unanticipated U.S. interest rate shocks and assesses their propagation to emerging economies. While anticipated shocks are “news” which have a delayed effect on the U.S. interest rate but affect on impact agents’ expectations, unanticipated shocks are “surprises” which change the U.S. interest rate contemporaneously.

To identify anticipated and unanticipated shocks, I use data from the Fed Funds Future contracts. First, I compute the anticipated change of the Fed Funds rate between two consecutive quarters and show that it contains useful information to explain its realized changes. Analogously, the unanticipated change is defined as the one step ahead forecast

¹See for example: [Canova \(2005\)](#), [Uribe and Yue \(2006\)](#), [Mackowiak \(2007\)](#), [Ilzetzki and Jin \(2013\)](#), and [Dedola, Rivolta, and Stracca \(2017\)](#).

error. Then, following a similar procedure to [Romer and Romer \(2004\)](#), I purge the anticipated and unanticipated policy movements of systematic policy changes which relate to current and expected U.S. business cycle conditions. The identified series of anticipated shocks contain important information to predict the narrative monetary policy shocks of [Romer and Romer \(2004\)](#), updated by [Tenreiro and Thwaites \(2016\)](#).

Using a quarterly sample of emerging economies, I estimate a Panel VAR to identify the effects of the previously identified anticipated and unanticipated shocks on macroeconomic aggregates of emerging economies. The model assumes that these economies are small open economies, which implies that they do not influence the Fed Funds rate. The baseline specification includes the main macroeconomic variables (GDP, Investment, Trade Balance, and CPI), the exchange rate, country interest rate, and cross-border bank flows. I incorporate the exogenous shocks in an exogenous block. Results show that emerging economies react once they receive the news about the future evolution of the Fed Funds, even before the rate changes. In particular, an expected 25 basis points increase of the U.S. interest rate induces a fall of 0.5% in GDP, coupled with an exchange rate depreciation and an increase in sovereign spreads, one quarter before the shock materializes. Unanticipated contractionary interest rate shocks also cause a similar contraction in emerging economies but after the change in the U.S. interest rate. The financial channel, through the country interest rate and the cross-border bank flows, is key to explain these adjustments.

In the second part of the analysis, I develop a two sector (i.e. tradable and non-tradable) small open economy model augmented with a banking sector to assess the transmission of U.S. interest rate shocks. In particular, banks borrow in international financial markets and lend to domestic firms. The key mechanism in the model to explain the empirical findings is based on financial frictions. When there is an anticipated or unanticipated increase in the international interest rate, the sovereign spread increases and the exchange rate depreciates. The latter deteriorates the bank's balance sheet because their liabilities are denominated in foreign currency while their assets are in the domestic one, a fact that has been labelled as currency mismatch. Since banks are subject to an incentive compatibility constraint, which relates the amount of debt they can issue to their net worth, they have to tighten their credit supply. On the one hand, the depreciation of the exchange rate fosters exports and a reallocation of resources towards the tradable sector. On the other hand, tradable firms rely on bank credit to finance their working capital constraint and are forced to restrict their production. Thus, expected and unexpected changes in the international interest rate induce an immediate decline in GDP of both tradable and non-tradable sectors. In this framework, I show that the feedback of domestic macroeconomic

conditions to the sovereign spread together with the working capital constraint are key to explaining the observed dynamics.

The international macroeconomics literature has so far assessed the propagation of U.S. monetary policy to emerging economies without reaching a conclusive evidence. On the one hand, [Canova \(2005\)](#) and [Ilzetzi and Jin \(2013\)](#), using different identification schemes, find that a contractionary shock induces an increase in the domestic interest rate, a depreciation of the exchange rate, and a delayed positive effect on economic activity in emerging economies after 1990. On the other hand, [Uribe and Yue \(2006\)](#) estimate the effects of changes in the U.S. real interest rate and claim that an increase in this rate induces a contraction of GDP in an emerging economy. [Mackowiak \(2007\)](#) and [Dedola, Rivolta, and Stracca \(2017\)](#) show that U.S. monetary policy shocks induce heterogeneous effects on real activity. In this paper, I show that anticipation is key to understand the effects of U.S. interest rate shocks and that an increase in the rate has a contractionary effect on emerging economies. Moreover, the financial channel, via the country interest rate and cross border bank flows, is key for the transmission of these shocks.

Sharp declines in capital inflows, called Sudden Stops, have been considered a major concern for emerging economies (see for example [Calvo, Izquierdo, and Talvi \(2006\)](#)). Usually, they induce immediate output collapses and severely affect the banking sector. The transmission channels and macroeconomic effects identified in this paper are consistent with the findings in this literature (see [Chari, Kehoe, and McGrattan \(2005\)](#); [Kehoe and Ruhl \(2009\)](#)). More recently, [Rey \(2013\)](#) and [Miranda-Agrippino and Rey \(2015\)](#) show that capital flows, especially credit flows, are largely driven by a *Global Financial Cycle*, which is determined by monetary conditions and by changes in risk aversion and uncertainty. Anticipated and unanticipated U.S. interest rate shocks may be key determinants of the *Global Financial Cycle* since they induce large declines in cross border bank flows and increases in sovereign spread.

There has been a renewed interest in the effects of news shocks, understood as shocks that are observed before they materialize ([Beaudry and Portier \(2006\)](#)). [Schmitt-Grohe and Uribe \(2012\)](#) show that anticipated shocks account for half of the predicted aggregate macroeconomic fluctuations. Following this line, many papers have tried to disentangle the effects of news shocks on different macroeconomic variables. For example, in an open economy framework, [Ben Zeev, Pappa, and Viccondoa \(2016\)](#) highlight the role of terms of trade news shocks to account for business cycles fluctuations in emerging economies. Regarding monetary policy, previous studies have analyzed the effects of unanticipated shocks to the interest rate rule in a closed-economy DSGE framework. [Milani and Treadwell \(2012\)](#) and [Gomes, Iskrev, and Mendicino \(2013\)](#) find that anticipated (news) shocks

in monetary policy are more important than unanticipated (surprise) ones to explain U.S. output fluctuations. This paper confirms that anticipated interest rate shocks have significant effects on business cycles of emerging economies.

Finally, my analysis is also related to the the strand of the literature that analyzes the effects of external shocks on small open economies. [Neumeyer and Perri \(2005\)](#) and [Uribe and Yue \(2006\)](#) show that shocks to both U.S. interest rate and country spreads are crucial drivers of business cycles in these economies. These works analyze shocks to the real interest rate while in this paper, in line with the empirical analysis, I consider the dynamics of the U.S. nominal interest rate and inflation separately. [Chari, Kehoe, and McGrattan \(2005\)](#) and [Kehoe and Ruhl \(2009\)](#) demonstrate that a Real Business Cycle model, augmented with labor market frictions and capacity utilization, cannot generate the observed GDP dynamics of Mexico after the Tequila Crisis. In particular, they suggest that financial frictions may be key to match the observed dynamics.² [Fernández and Goulan \(2014\)](#) state that the financial accelerator is important in small open economy models to explain the countercyclicality of interest rates. In this paper, I consider the interaction of the financial accelerator mechanism with other financial frictions to match the empirical findings. Following [Shousha \(2016\)](#), I augment a small open economy model with a banking sector and consider in the analysis the following financial frictions: working capital constraint, currency mismatch, bank's incentive compatibility constraint, and the dynamics of the country interest rate. I depart from the model developed by [Shousha \(2016\)](#) by considering a non-tradable sector that is subject to monopolistic competition, which creates a role for the nominal interest rate and monetary policy, and by assuming a different production structure and country interest rate dynamics. Moreover, the main findings are robust to different parametrizations of financial frictions and elasticities.

The remaining of this paper is organized as follows. Section 1.2 describes the identification and properties of news and surprise U.S. interest rate shocks and compares them with the narrative series of monetary policy shocks. Section 1.3 characterizes the empirical strategy used to identify the macroeconomic effects of both types of shocks on emerging economies and displays the empirical results. Section 1.4 presents a theoretical model that replicates the empirical findings and explains the transmission mechanism. Finally, Section 1.5 concludes.

²In this line, [Gertler, Gilchrist, and Natalucci \(2007\)](#) find that the financial accelerator mechanism accounts for half of the observed decline in economic activity in South Korea during the Asian financial crisis of 1997/98.

1.2 Identification of News and Surprise U.S. Interest Rate Shocks

In this section, I describe the strategy used to identify news and surprise U.S. interest rate shocks. First, I compute anticipated and unanticipated movements in the U.S. interest rate using information from Fed Funds future markets. However, expectations about movements in this interest rate capture expected reaction of the Federal Reserve to anticipated changes in U.S. business cycle conditions. Then, I use market's expectations regarding U.S. main macroeconomic variables to purge pure U.S. interest rate shocks from the systematic changes. Finally, I assess the properties of this series by comparing it to the narrative series of monetary policy shocks.

1.2.1 Anticipated and Unanticipated Movements in U.S. Interest Rate

To capture private sector's expectations about the evolution of U.S. interest rate, I use data from the Chicago Board of Trade (CBOT) Fed Funds Future Market for different maturities. [Hamilton \(2009\)](#) shows that these contracts are an excellent predictor of the Fed Funds rate. Unlike using a time series model (like VARs) to compute expectations about interest rates, market-based forecasts have the advantage of adapting to changes in the FED's reaction to the state of the economy (i.e. potential time varying parameters in the Taylor rule, see [Cochrane and Piazzesi \(2002\)](#)).

The price of the Fed Funds future contracts is based on the average monthly Federal Funds interest rate. At the beginning of a month, these prices are based primarily upon future expectations about the Fed Funds effective rate in that month.³ Considering that I want to compute market's expectation for each quarter, I use the price of Fed Funds futures at the beginning of each period for all the available horizons and I compute an average of

³See [Owens and Webb \(2001\)](#) and "Reference Guide: CBOT Fed Fund Futures" for a detailed description on how this market works. One potential source of concern is that the risk premia may drive a wedge between the price of Fed Funds future contracts and the expected rate. [Sack \(2004\)](#) documents the existence of a time varying risk premia in Fed Funds futures but its impact on prices is fairly limited, specially in short maturities. Moreover, the risk premia does not vary significantly across short-term maturities, like the ones used in this paper. [Piazzesi and Swanson \(2008\)](#) show that these excess returns are strongly countercyclical and can be predicted by macroeconomic indicators. In this paper, considering that I use the difference in the price of these contracts (not the level) and that there is no consensus on how to effectively remove the premium, I do not adjust future prices by risk premia. However, as I show in section 1.2.2, I purge the anticipated and unanticipated movements in the rate from expected and unexpected business cycle fluctuations. Moreover, as robustness exercise in section 1.3.4.3, I consider an specification that includes the VIX and U.S. GDP together with the interest rate shocks.

all the contracts that belong to that quarter.⁴ The anticipated change of this variable over time is defined as:

$$\Delta i_{t,j}^a = \mathbb{E}_{t-1}(i_{t+j} - i_{t+j-1}) \quad \text{for } j = \{0, 1, 2, 3\} \quad (1.1)$$

where $\Delta i_{t,j}^a$ denotes the anticipated movement in the fed funds rate j quarters ahead with respect to the previous one and $\mathbb{E}_{t-1}(i_{t+j})$ represents the expected value of the Fed Funds rate for the period $t+j$ conditional on the information available from the previous period. On the other hand, I define an unanticipated (surprise) movement as:

$$\Delta i_t^u = i_t - \mathbb{E}_{t-1}i_t \quad (1.2)$$

where Δi_t^u denotes the unanticipated movement in the Fed Funds rate, which is defined as the difference between the realized rate and the one agents were expecting at the beginning of the quarter. Figure 1.1 displays the dynamics of the anticipated movement of the interest rate at the beginning of the quarter and the realized one.⁵

Markets tend to anticipate quite accurately the evolution of the Fed Funds rate in the incoming quarter. The contemporaneous correlation between the anticipated movement and the realized one is 0.89. Moreover, anticipated movements explain 80% of realized Fed Funds fluctuations. This fact reinforces the relevance of considering anticipation to assess the effects of interest rate shocks. As expected, unanticipated movements, which correspond to the difference between the line and the bars in Figure 1.1, occur mostly during recessions, when it is more difficult to predict the evolution of monetary policy.⁶

A crucial issue is to determine which is the horizon of anticipation of fluctuations in the Fed Funds rate. For this reason, I estimate the current changes in this rate on the expected change made at the beginning of the current quarter and on the previous three quarters. Table 1.1 displays the results.⁷

The predictive power of forecasts about the change in the Fed Funds rate decline significantly with the horizon. While the contemporaneous and two periods ahead forecasts explain a significant fraction of the realized change, the one made three quarters ahead

⁴For example, for the first quarter of 1995, I take the end of the day prices of January 3, which was the first active day of the quarter. I use the front, 2nd, and 3rd continuous contracts to compute expectations about the current quarter interest rate. The 4th, 5th, and 6th and 7th, 8th, and 9th contracts are used, respectively, to compute expectations regarding the next 2 following quarters. Contracts longer than nine months ahead are significantly less liquid.

⁵Note that $\Delta i_t = i_t - i_{t-1} = \Delta i_{t,0}^a + \Delta i_t^u$

⁶Appendix A.3 displays the dynamics of the identified unanticipated U.S. interest rate shocks.

⁷In Table 1.1 I report only the Adj. R^2 and the F-Statistic because I focus on the power of the forecasts to explain the realized evolution of the interest rate.

provides noisy information. Thus, in the empirical analysis, I consider two quarters ahead anticipation for changes in the U.S. interest rate.

1.2.2 Identifying U.S. Interest Rate Shocks

Some fluctuations of the U.S. interest rate are due to changes in business cycle conditions in the U.S. economy (i.e. they reflect the systematic response to other shocks that affect the U.S. economy). These changes in the interest rate cannot be considered an interest rate shock since they capture the systematic response of the FED to global demand or supply shocks. Thus, I purge anticipated and unanticipated changes in the U.S. interest rate from the ones that are due to expected and unexpected macroeconomic dynamics following a similar procedure to [Romer and Romer \(2004\)](#). In particular, I assume that the evolution of GDP, unemployment, and inflation are the key indicators that the FED is likely to consider when settling the policy. Then, I can identify anticipated and unanticipated shocks by estimating the following equations:⁸

$$\Delta i_t^u = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 (\hat{y}_t - \mathbb{E}_{t-1} \hat{y}_t) + \alpha_3 (\hat{u}_t - \mathbb{E}_{t-1} \hat{u}_t) + \alpha_4 (\hat{\pi}_t - \mathbb{E}_{t-1} \hat{\pi}_t) + (\epsilon_t - \mathbb{E}_{t-1} \epsilon_t) \quad (1.3)$$

$$\begin{aligned} \Delta i_{t,i}^a = & \gamma_{0,i} + \gamma_{1,i} \mathbb{E}_{t-1} (i_{t+i-1}) + \gamma_{2,i} \mathbb{E}_{t-1} (\hat{y}_{t+i} - \hat{y}_{t+i-1}) + \gamma_{3,i} \mathbb{E}_{t-1} (\hat{u}_{t+i} - \hat{u}_{t+i-1}) + \\ & \gamma_{4,i} \mathbb{E}_{t-1} (\hat{\pi}_{t+i} - \hat{\pi}_{t+i-1}) + \mathbb{E}_{t-1} (\epsilon_{t+i} - \epsilon_{t+i-1}) \quad \forall i = \{0, 1, 2\} \end{aligned} \quad (1.4)$$

Equation (1.3) decomposes the unanticipated change between unexpected movements in GDP growth (\hat{y}_t), unemployment (\hat{u}_t), inflation ($\hat{\pi}_t$), and the unanticipated interest rate shock ($\epsilon_t - \mathbb{E}_{t-1} \epsilon_t$). Equation (1.4) expresses an anticipated change as a function of expected changes in the same macroeconomic variables for the different horizons ($i = \{0, 1, 2\}$) plus the anticipated interest rate shock.

Anticipated and unanticipated changes in the U.S. interest rate are computed using market's expectations. Thus, to estimate equations (1.3) and (1.4) with the same information set, I would like to consider private sector's expectations about the evolution of the main macroeconomic variables mentioned before. For this reason, I use the Survey of Professional Forecasters (SPF) data set, a quarterly survey of macroeconomic forecasts published by the Federal Reserve Bank of Philadelphia. This data set, which has been widely used in previous studies, contains forecasts by quarter up to one year ahead of the main macroeconomic variables in the U.S. conditional on the information available from the previous quarter.⁹

⁸Appendix A.2 contains a detailed derivation of both expressions, assuming a simple Taylor rule.

⁹This data set asks to professional forecasters their expectations about the evolution of macroeconomic variables for the following quarters during the first month of the ongoing quarter. In order to use expectations that

All equations are estimated by OLS and I identify the residuals of each of them, the last terms, as the unanticipated and anticipated U.S. interest rate shocks. One source of concern is the potential feedback between expected changes in the rate and in macroeconomics dynamics. However, each equation contains macroeconomic forecasts for the same horizon. Considering that there is some lag in the effects of monetary policy, this makes it unlikely that the estimated coefficients are biased due to simultaneity.¹⁰ Moreover, the objective of these regressions is not to estimate the FED's response function but to purge anticipated and unanticipated changes in the U.S. interest rate of movements due to expected changes in U.S. macroeconomic conditions. In this context, the identified series of shocks capture a variety of factors like perceived overreaction or underreaction and/or temporary shifts in the priorities of the FED.

This way of identifying anticipated and unanticipated shocks differs from the identified monetary policy surprises defined by Gurkaynak, Sack, and Swanson (2005). They identify two components of monetary policy: a "current Fed Funds rate target" and a "future path of policy", by extracting two factors that explain the variability of a set of Fed Funds futures for different maturities. However, their approach is not directly comparable to mine since they do not distinguish the exact timing of the policy path (i.e. in which particular month markets expect an increase in the interest rate). Considering the aim of this paper and that U.S. interest rate is exogenous for small open economies, I employ a different complementary strategy. First, I do not focus on particular events and my strategy is more comparable to the VAR literature on monetary policy shocks (see Kuttner (2001)). Second, instead of computing the difference in price for the same contract, I calculate the one across different maturities at the beginning of the quarter. Thus, anticipated movements capture market's expectations about the evolution of the Fed Funds rate incorporating all the available information at that particular date. Third, markets may have already incorporated all the important information by the time of the FOMC meeting and, in this case, the surprise defined by Gurkaynak, Sack, and Swanson (2005) would be zero. However, this fact does not mean that there is no expected change in the monetary policy stance for emerging economies.

are aligned with the computation of expected interest rate, I employ the forecasts after the first release of macro data from the previous quarter. The main advantage of this data set is that it contains expectations for each variable and quarter up to one year ahead. For this exercise, I use expectations about GDP growth, Unemployment rate and GDP deflator inflation rate. See <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/> for more detailed information about this survey.

¹⁰The evidence about the lag in the effects of monetary policy in the U.S. is robust across different identification assumptions (see for example Romer and Romer (2004)).

1.2.3 Comparison with Series of Monetary Policy Shocks

Previous studies have used different empirical strategies to identify U.S. monetary policy shocks. The narrative series of [Romer and Romer \(2004\)](#), updated by [Tenreiro and Thwaites \(2016\)](#)(TT(2016)), is one of the most popular ones.¹¹ This series is defined as changes in the reference interest rate at FOMC meetings that are not endogenous reactions to fluctuations in the economy. In particular, [Romer and Romer \(2004\)](#) remove the discretionary policy changes that were responding to the fluctuations in macroeconomic variables within policy makers' information set. Table 1.2 displays the contemporaneous correlation between this series and the interest rate shocks I identified in the previous subsection.¹²

The first fact that emerges is that the anticipated series about the current quarter is highly and significantly (0.69) correlated with TT(2016) series. Moreover, the correlation of TT(2016) is still positive and significant with respect to the anticipated series made one period in advance. Second, the unanticipated series is also positive correlated with TT(2016) series, which means that a fraction of TT(2016) can be considered unanticipated. Finally, an important fact for the analysis is that surprise and anticipated shocks are orthogonal.

The anticipated series are made at the beginning of each quarter, before the realization of TT(2016) series for the same quarter, and are orthogonal to unanticipated shocks.¹³ These facts may help to disentangle the relationship between these series and TT(2016). In particular, I test whether the series identified in this paper contain useful information to predict the narrative ones. To test this hypothesis formally, I estimate the following equation:

$$TT_t = \alpha + \beta Shock_t + \epsilon_t$$

where $Shock_t$ denotes $\{\Delta i_{t,0}^a, \Delta i_{t-1,1}^a, \Delta i_{t-2,2}^a\}$, the predictions about the evolution of the interest rate made at the beginning of this quarter and at the previous ones, and TT_t denotes the contemporaneous series of TT(2016).¹⁴ The shocks proposed in this paper contain useful information to predict the other series if the β is statistically significant. Table 1.3 displays the results of these regressions:

¹¹The series can be downloaded from: <https://www.aeaweb.org/articles?id=10.1257/mac.20150016>.

¹²Appendix A.3 displays the anticipated and unanticipated shocks together with the narrative series of monetary policy shocks. Similar results hold if I use the anticipated and unanticipated changes in the U.S. interest, without the orthogonalization proposed in Section 1.2.2.

¹³The narrative series of monetary policy shocks of TT(2016) are computed for each FOMC meeting, which takes place after the first day of each quarter.

¹⁴Results are robust if I add lags of TT(2016) series to the regression.

The current quarter and the one quarter ahead anticipated interest rate shocks contain useful information to predict TT(2016) series.¹⁵ In particular, anticipated shocks explain up to 47% of the observed fluctuations in TT(2016) shocks. In line with the results of Table , the closer to the quarter, the more precise is the forecast. Given these results, including only the current value of any of these shocks or the narrative series may not be enough to describe the dynamic response of macroeconomic variables. Since markets forecast quite accurately the changes in the U.S. interest rate, emerging economies could start reacting to these shocks even before the change materializes. This fact should be reflected immediately in high frequency variables and may also affect contemporaneous macroeconomic variables.

1.3 Empirical Analysis

This section presents the estimated macroeconomic effects of news (anticipated) and surprise (unanticipated) U.S. interest rate shocks, identified in the previous section, on emerging economies. First, I specify the empirical model used to assess the effects of both types of shocks on emerging economies. Then, I describe the estimation method and the data set. Finally, I present the Impulse Response Functions (IRFs) of the main macroeconomic variables of emerging economies to both types of shocks.

1.3.1 Empirical Model

The empirical model is a VAR system that includes both anticipated and unanticipated interest rate shocks identified in Section 1.2.2 in an exogenous block:

$$X_t = B + C(L)X_{t-1} + D(L)\Delta i_t^u + E(L)\Delta i_{t,0}^a + F\Delta i_{t,1}^a + G\Delta i_{t,2}^a + \epsilon_t \quad (1.5)$$

where X_t is a vector of endogenous variables, $C(L)$, $D(L)$, $E(L)$ denote P-order lag polynomials, and Δi_t^u and $\Delta i_{t,j}^a$ are the surprise and anticipated interest rate shocks, respectively. Following the results of Table 1.1, I consider only two quarters as the anticipation horizon for U.S. interest rate shocks. Finally, ϵ_t is a white noise vector of disturbances. This system is similar to the one proposed by [Mertens and Ravn \(2012\)](#) to study the effects of anticipated and unanticipated tax shocks in the U.S. In order to allow for persistence in the changes in U.S. interest rate, the system includes lags of both shocks (i.e. Δi_t^a and Δi_t^u).¹⁶

¹⁵The regressions have less observations because the TT(2016) series finishes in December 2007.

¹⁶In the baseline specification, I include one lag of each shock. However, results are robust to not including any lags or allowing for more lags.

This specification is in line with small open economy models and with previous empirical studies that consider changes in U.S. interest rate as exogenous for emerging economies. One of its main advantages is that the effects of these shocks do not rely on the ordering of the variables. In particular, there is no need to impose zero or sign restrictions on the reaction of domestic variables to changes in U.S. interest rate, nor to identify the other shocks in the system.

In the baseline specification, X_t is defined as:

$$X_t = [\text{Credit}_t, \text{TOT}_t, \text{GDP}_t, I_t, \frac{\text{TB}_t}{\text{GDP}_t}, \text{NEER}_t, \text{CPI}_t, R_t]$$

where Credit_t denotes the cross-border bank flows to the whole economy, TOT_t is the terms of trade of the country, I_t represents investment, $\frac{\text{TB}_t}{\text{GDP}_t}$ is the ratio of trade balance to GDP, NEER_t denotes nominal exchange rate, CPI_t represents Consumer Price Index, and R_t denotes the country nominal interest rate.¹⁷ This set of variables is necessary to capture both the macroeconomic effects (both on economic activity and inflation) and the transmission channels (financial and trade channels).

1.3.2 Estimation Method

I estimate the VAR presented in (1.5) by pooling quarterly data from Argentina, Brazil, Chile, Mexico, Philippines, South Africa, and Turkey. The sample begins in the first quarter of 1995, when the FED explicitly started to announce its target level for the Fed Funds rate, and ends in the second quarter of 2014.¹⁸ The choice of countries is guided by macroeconomic and financial data availability to construct a representative sample of emerging economies, similar to the ones used by [Uribe and Yue \(2006\)](#) and [Akinci \(2013\)](#). I estimate the system with quarterly data in order to capture more precisely the transmission channels and the macroeconomic effects. Precise definitions of the variables and data sources are included in Appendix A.1.

The system is estimated using the Least Square Dummy Variable (LSDV) estimator or fixed effects estimator, which has been widely used to estimate Panel VARs with a large time series dimension. As this dimension is significantly larger than the cross-sectional one, the LSDV is preferred to GMM as it has better finite sample properties. [Nickell \(1981\)](#)

¹⁷A reduction (increase) in the FX indicates a depreciation (appreciation) of the domestic currency. Results are robust if I use the Capital Flight computed from the Balance of Payments instead of Cross-Border Bank Flows. The country interest rate is defined as the ten year U.S. government bond yield plus the country spread, proxy by the JP Morgan EMBI Global Index. Appendix A contains a detailed description of the sources of each series.

¹⁸The sample for each country depends on data availability. Prior to 1995 there is no availability of continuous series of future contracts for nine months ahead. Appendix A.1 contains a detailed description of the sample used for each country.

shows that a potential concern with the Panel VAR is the inconsistency of the least squares parameter estimates due to the combination of fixed effects and lagged independent variables. However, because the time series dimension of the dataset is large (78 observations), the inconsistency problem is likely not to be a major concern.

The estimation procedure imposes that $C(L)$, $D(L)$, $E(L)$, F and G are the same across countries. This assumption seems appropriate since estimations using different country groups yield similar results for news and surprise shocks.¹⁹ Considering the information criteria, I estimate a VAR with 2 lags.²⁰

1.3.3 Impulse Responses

In this subsection, I present the macroeconomic responses of emerging economies to the anticipated and surprise shocks identified in Section 1.2.2. Figure 1.2 displays the reaction of macroeconomic variables to a two quarters ahead anticipated 25 basis points (one standard deviation) contractionary U.S. interest rate shock.

The anticipated contractionary shock induces an immediate contraction of GDP and investment of approximately 0.5% and 1.3%, respectively, from their linear trends. These results are partially explained by the immediate reduction in the cross border bank flows and the depreciation of the nominal exchange rate. The country interest rate also increases and reaches its peak one quarter after the shock, which means that the country spread raises before the change in the international interest rate materializes at $t = 0$.²¹ An important fact to highlight is that most of the adjustment of these variables occurs within the first two quarters. The trade balance to GDP ratio improves only when the change in the international interest rate materializes and could also be explained by the previous 1.25% depreciation of the nominal exchange rate. Finally, the contractionary effect does not have any significant effect on terms of trade but reduces significantly the consumer price index. From this analysis, the financial channel, via cross border bank flows and the country interest rate, is important to understand the adjustment of macroeconomic variables.²²

Macroeconomic variables display similar dynamics than in case of a Sudden Stop (Calvo (1998)). This phenomenon is characterized by a sudden slow down in private capital inflows that is followed by a sharp decrease in GDP and investment, a real exchange

¹⁹To test that the results are not driven by outliers, I have estimated the system dropping one country at the time. Results, presented in the Online Appendix, are robust and no particular country seems to be affecting the results.

²⁰The Akaike Information Criterion (AIC) chooses 2 lags while the Bayesian Information Criterion (BIC) and the Hannan-Quinn (HQ) choose 1 lag. Reduced form residuals are not autocorrelated with the two lags specification but not including only one lag. Results are robust to a specification that includes 4 lags.

²¹The country spread is the difference between the domestic and the U.S. interest rate for the same maturity.

²²In Section 1.4.5 I assess the relevance of the financial channel for the transmission of the shocks using a small open economy model.

rate depreciation, and an improvement in the current account. Although I do not consider capital inflows in my analysis, the fast decline and recovery of macroeconomic variables and the cross border bank flows dynamics are consistent with the findings of this literature. In particular, anticipated movements in the interest rate may trigger Sudden Stops. Figure 1.3 displays the IRFs to an unanticipated 25 basis points (one standard deviation) contractionary U.S. interest rate shock.

In this case, the reaction is also immediate and reaches its minimum two quarters after the shock. For most of the variables the adjustment is quantitatively similar to the anticipated shock. Unlike the previous case where variables converge fast, in this case the shock has a slightly more persistent effect on GDP and investment, taking around six quarters to converge to their trends. The persistence might be induced by the depreciation of the exchange rate and the delayed reduction of cross border bank flows. Unlike the findings of [Uribe and Yue \(2006\)](#) and [Akinici \(2013\)](#), country interest rate does not display a delayed reaction to the unanticipated shock. This fact, which coincides with the findings of [Canova \(2005\)](#) and [Mackowiak \(2007\)](#), is consistent with the idea that financial variables react on impact to the new flow of information. Finally, as in the previous case, terms of trade do not react significantly to changes in the U.S interest rate. The lack of significant response, which may be surprising given that most of these countries are commodity exporters and commodity prices are sensible to U.S. monetary policy ([Frankel \(2006\)](#)), could be due to the lack of adjustment of manufacturing prices. Overall, the financial channel, through the country interest rate and the cross-border bank flows, is important for the transmission of both types of interest rate shocks, confirming the findings of [Canova \(2005\)](#).

1.3.4 Alternative Empirical Specifications

Both contractionary anticipated and unanticipated contractionary U.S. interest rate shocks induce a contraction of economic activity in emerging economies. This fact could be due to the unconventional monetary policies during the crisis of 2008, the definition of the U.S. interest rate shock, global financial conditions ([Akinici \(2013\)](#)), global changes in economic activity that affect the U.S. interest rate, exchange rate regime, and/or the particular set of countries considered in the analysis. In this section, I show that the main findings of the previous section are not due to these reasons. Section 1.3.4.1 presents the results for the Zero Lower Bound (ZLB) sample, one of the main concerns. For ease of exposition, I only present the cumulative responses of variables to anticipated and unanticipated shocks for the rest of the specifications in Tables 1.4 and 1.5, leaving the impulse responses for the Online Appendix.

1.3.4.1 Pre-Crisis Sample

Since 2008, the Federal Reserve has implemented unconventional monetary policies to boost the economy, which could represent a break in the transmission of monetary policy and could be behind previous findings. In order to examine whether previous results are sensitive to the inclusion of the ZLB period, I estimate the baseline VAR of Section 1.3.3 but restricting the period of analysis up to 2007.Q4, before reaching the ZLB. Figure 1.4 displays the IRFs to an anticipated contractionary interest rate shock together with the results from the full sample.

The responses of the main macroeconomic variables to the anticipated shock before $t = 0$ (i.e. the period when the U.S. interest rate increases by 0.25%) remain unchanged. However, GDP increases slightly when the shock hits the economy, in line with the findings of [Ilzetzki and Jin \(2013\)](#) for this period. This reaction could be explained by the lack of response of the nominal exchange rate and the less persistent reaction of cross border bank flows. Thus, missing the anticipation effects in this case distorts the assessment of the effects of these shocks. Similar to the full sample, most of the adjustment occurs before the change in the U.S. interest rate materializes. Figure 1.5 displays the response to an unanticipated contractionary interest rate shock.

Responses are also similar for the unanticipated shock but slightly less significant than in the baseline results. This fact can be explained by the lack of depreciation of the nominal exchange rate and the shorter sample, which leads to less precise estimates. However, impact responses are comparable both qualitatively and quantitatively between both samples.

1.3.4.2 Definition of the Interest Rate Shock

In Section 1.2.2, I have orthogonalized anticipated and unanticipated movements in the U.S. interest rate from market's expectations to control for policy reactions due to business cycle conditions. However, any movement in the U.S. interest rate, as defined in Section 1.2.1, can be considered exogenous for a small open economy since what happens in each of these countries does not affect the international interest rate. To examine whether movements in the U.S. interest rate have the same impact as U.S. interest rate shocks, I estimate the VAR including the anticipated and unanticipated movements in the interest rate, as defined in Section 1.2.1, instead of the interest rate shock series, as defined in 1.2.2 (i.e. without orthogonalizing the anticipated and unanticipated movements in the Fed Funds). The second column of Tables 1.4 and 1.5 shows the cumulative response of GDP using this

alternative definition of interest rate shocks. Results are slightly stronger for the anticipated movement and weaker for the surprise one. Overall, responses are comparable to the ones using the U.S. interest rate shocks.

1.3.4.3 Global Financial Conditions and Global Shocks

[Akinci \(2013\)](#) shows that global financial risk, proxied by the U.S. BAA corporate spread, explains around 20% of aggregate fluctuations in emerging economies and that the role of risk-free interest rate shocks is negligible. First, I check the effect of the identified interest rate shocks on this variable and find that each contractionary shock increases the BAA Spread reaching its maximum on impact.²³ Then, considering that this variable is exogenous for an emerging economy, I estimate the baseline VAR adding the U.S. BAA Spread Indicator in an exogenous block to test whether financial conditions are driving the results presented in Section 1.3.3. The third column of Tables 1.4 and 1.5 displays the cumulative responses of macroeconomic variables to both types of interest rate shocks. While responses to the anticipated shock are similar both qualitatively and quantitatively to the baseline case, the ones to an unanticipated shock are less statistically significant. This result could be explained by the fact that most of the unanticipated interest rate shocks coincide with U.S. recession times, when corporate spread also peaks.

Alternatively, [Miranda-Agrippino and Rey \(2015\)](#) show that credit flows are largely driven by a global factor, which can be related to U.S. monetary conditions and changes in risk aversion and uncertainty. Thus, I assess whether the previous results are driven by this global factor or by the identified shocks by estimating the baseline VAR including the global factor in the exogenous block. The fourth column of Tables 1.4 and 1.5 displays the cumulative responses of macroeconomic variables to both types of interest rate shocks. Responses to both shocks remain unchanged, supporting the findings that monetary policy in the U.S. is one of the drivers of this global factor.

Finally, results could be driven by aggregate shocks to global activity and/or changes in global volatility. To assess these hypotheses, I include World GDP and the CBOE Volatility Index (VIX) one at a time in the exogenous block of the VAR.²⁴ Columns five and six of Tables 1.4 and 1.5 display the cumulative responses to both types of shocks for these specifications. Responses are comparable for all the variables and for both shocks.

²³Moody's Seasoned BAA Corporate Bond yield relative to yield on 10-Year Treasury Constant Maturity. Source: FRED. Figure A.2 included in Appendix A.4 displays the IRFs of this variable to both shocks.

²⁴For World GDP I use the growth rate of world GDP computed by the IMF.

1.3.4.4 Extended Sample of Emerging Economies

Results could also be driven by the particular sample of countries. To entertain this hypothesis, I estimate the same VAR but extending the sample to other emerging economies that are part of the JP Morgan EMBI Global index. In particular, I add the following countries to the previous sample: Bulgaria, Colombia, Ecuador, Hungary, Republic of Korea, Malaysia, Peru, and Thailand.²⁵ The seventh column of Tables 1.4 and 1.5 displays the cumulative responses to both types of shocks.

The magnitudes of adjustment for most of the variables to an anticipated shock are slightly lower but the persistence is very similar. In particular, cross border bank flows, exchange rate and trade balance to GDP ratio react slightly less than in the baseline specification. Responses to the unanticipated shock are comparable to the baseline ones.

1.3.4.5 Exchange Rate Regime

The reaction of emerging economies to anticipated and unanticipated U.S. interest rate shocks could depend on their exchange rate regime. To test this hypothesis, I estimate the baseline VAR for a subsample of countries with fixed exchange rate regimes. Following the classification developed by [Ilzetzi, Reinhart, and Rogoff \(2017\)](#), I consider fixed exchange rate regimes countries classified as “Pre-Announced Peg” or “Crawling Peg +/- 2%” in the Coarse Classification.²⁶ The eighth column in Tables 1.4 and 1.5 displays the cumulative responses to both types of shocks for this sample of countries.

Despite no significant cumulative response of the nominal exchange rate, the remaining variables react in a similar way to the baseline specification. Most variables respond to the unanticipated shock less significantly, partially due to the reduced number of observations. The stronger reaction of the country interest rate to the unanticipated shock suggests that markets perceive more risk in these economies relative to the ones with flexible exchange rate regime. Finally, considering that the nominal exchange rate does not adjust, these countries experience a slightly stronger adjustment in prices in response to this shock. Then, the results show that the responses of emerging economies do not depend qualitatively on their exchange rate regime, confirming the findings of [Canova \(2005\)](#) and [Dedola, Rivolta, and Stracca \(2017\)](#).

²⁵The period of the sample remains 1995:1-2014:2. As in the previous case, the periods for each country differ according to JP Morgan EMBI Global index availability.

²⁶The sample consists of 194 observations: Argentina 1995:Q1-2001:Q4, Brazil 1996:Q1-1998:Q4, Ecuador 2000:Q1-2013:Q4, Peru 1997:Q1-2014:Q2, Philippines 2001:Q1-2006:Q4.

1.4 Theoretical Model

In this section, I develop a small open economy model to characterize the adjustment of emerging economies to U.S. interest rate shocks. This is a dynamic stochastic model with two production sectors (tradable and non-tradable) and a financial intermediary similar to the one presented in [Gertler and Kiyotaki \(2010\)](#) and [Shousha \(2016\)](#). In order to fully focus on the transmission of these shocks, I follow [Uribe and Yue \(2006\)](#) and feed into the model the estimated equation that describes the dynamics of R_t from the VAR (equation (1.5)). Therefore, the dynamics of the country interest rate is an exogenous process that depends on U.S. interest rate, GDP, investment, trade balance, the real exchange rate, and the cross-border bank flows. Providing a more microfounded specification of country spreads is outside the scope of this model.

The main assumptions of the model can be summarized as follows. First, there are three different types of goods: exportable, non-tradable, and importable. While the first two goods are produced domestically, the latter is imported and used by tradable firms. This assumption enables me to define appropriately the terms of trade and the real exchange rate faced by this economy in order to compare with their empirical counterparts. Second, production sectors differ in their market structure. While the exportable sector is a price taker in international markets, non-tradable firms have market power and face quadratic price adjustment costs. This assumption can be rationalized by the fact that most emerging economies are mainly exporters of commodities for which they are price takers in international markets. Similar to [Garcia Cicco \(2010\)](#), price rigidities are necessary to introduce a role for the U.S. nominal interest rate and monetary policy. Third, tradable firms are subject to a working capital constraint, which generates supply-side effects due to the changes in external financial conditions ([Neumeyer and Perri \(2005\)](#); [Uribe and Yue \(2006\)](#)).²⁷ Fourth, the only shocks that affect this economy are the anticipated and unanticipated U.S. interest rate shocks. Lastly, following [Aoki, Benigno, and Kiyotaki \(2016\)](#) and [Shousha \(2016\)](#), banks borrow from international markets, subject to an incentive compatibility constraint, and lend to domestic firms.

An increase in the international interest rate, coupled with an exchange rate depreciation and an increase in the sovereign spread, reduces the access of banks to international

²⁷In the baseline model, non-tradable firms are not subject to a working capital constraint but they make positive profits in steady state. Considering that households are the owners of these firms and that they can borrow from abroad at R_t^* and that firms could potentially borrow only from the bank at $R_t > R_t^*$, households would prefer to retain profits to satisfy the working capital constraint. Nevertheless, I have also extended the model to allow for a working capital constraint for non-tradable firms and results remain unchanged.

financial markets and, thus, the supply of domestic credit. Similar to the dynamics experienced by emerging economies in case of a Sudden Stop (see, for example, [Kehoe and Ruhl \(2009\)](#)), the output of both the tradable and non-tradable sector fall.

1.4.1 The Model

Households

Following [Gertler and Kiyotaki \(2010\)](#) and [Gertler and Karadi \(2011\)](#), the representative household consists of a fraction f of workers and $(1 - f)$ of bankers. While workers supply labor to firms in exchange for wages, bankers manage domestic banks subject to the flow of funds constraint until retirement, which occurs with a probability $(1 - \sigma^B)$. There is perfect insurance between household members and they have preferences described by the following utility function (similar to [Greenwood, Hercowitz, and Huffman \(1988\)](#)):

$$U(c_t, h_t) = \frac{\left(c_t - bc_{t-1} - \frac{(h_t)^\omega}{\omega}\right)^{1-\sigma} - 1}{1 - \sigma}$$

where σ is the coefficient of relative risk aversion, b determines the degree of internal habit formation, h_t denotes hours worked, and ω determines the Frisch elasticity of labor supply. The consumption basket (c_t) is composed by consumption of tradable (c_t^T) and non-tradable (c_t^N) goods:

$$c_t = \left[\chi (c_t^T)^{1-\frac{1}{\mu}} + (1 - \chi) (c_t^N)^{1-\frac{1}{\mu}} \right]^{\frac{1}{1-\frac{1}{\mu}}} \quad (1.6)$$

where μ denotes the elasticity of substitution between the two types of goods. Besides consuming, households can demand public bonds (D_t^{pol}) and issue foreign debt (D_t^{H*}).²⁸ They are subject to the following budget constraint:

$$P_t^T c_t^T + P_t^N c_t^N + S_t R_{t-1}^* D_{t-1}^{H*} + D_t^{pol} = W_t h_t + R_{t-1}^{pol} D_{t-1}^{pol} + S_t D_t^{H*} + \sum_{j=\{T,N,B\}} \tilde{\Pi}_t^j + \frac{\phi^D}{2} (D_t^{*B} + D_t^{*H} - \bar{D})^2$$

where $\tilde{\Pi}_t^j$ denotes nominal profits from banks, tradable, and non-tradable firms, W_t is the nominal wage, R_t^i denotes the gross nominal interest rate of asset i , and S_t denotes the nominal exchange rate. The last term is the debt adjustment costs to foreign debt position in order to avoid a unit root on external debt ([Schmitt-Grohe and Uribe \(2003\)](#)). Finally, households are also subject to a no-Ponzi constraint:

²⁸ D_t^{H*} can be negative which means that households accumulate foreign assets.

$$\lim_{z \rightarrow \infty} \mathbb{E}_t \frac{D_{t+z+1}^{H*}}{\prod_{s=0}^z R_{t+s}^*} \leq 0$$

The Law of One Price holds in this economy. Thus, the price of the tradable good is: $P_t^T = S_t P_t^{T*}$. To simplify, I assume that $P_t^{T*} = 1$. Therefore, $P_t^T = S_t$. The corresponding first order conditions for consumption, labor supply decision, and demand of assets in real terms are:

$$\frac{P_t^T \lambda_t}{P_t} = \left(c_t - b c_{t-1} - \frac{(h_t)^\omega}{\omega} \right)^{-\sigma} \chi \left(\frac{c_t}{c_t^T} \right)^{\frac{1}{\mu}} - b \beta \left(c_{t+1} - b c_t - \frac{(h_{t+1})^\omega}{\omega} \right)^{-\sigma} \chi \left(\frac{c_{t+1}}{c_{t+1}^T} \right)^{\frac{1}{\mu}} \quad (1.7)$$

$$\frac{P_t^T}{P_t^N} = \frac{\left(c_t - b c_{t-1} - \frac{(h_t)^\omega}{\omega} \right)^{-\sigma} \chi \left(\frac{c_t}{c_t^T} \right)^{\frac{1}{\mu}} - b \beta \left(c_{t+1} - b c_t - \frac{(h_{t+1})^\omega}{\omega} \right)^{-\sigma} \chi \left(\frac{c_{t+1}}{c_{t+1}^T} \right)^{\frac{1}{\mu}}}{\left(c_t - b c_{t-1} - \frac{(h_t)^\omega}{\omega} \right)^{-\sigma} (1 - \chi) \left(\frac{c_t}{c_t^N} \right)^{\frac{1}{\mu}} - b \beta \left(c_{t+1} - b c_t - \frac{(h_{t+1})^\omega}{\omega} \right)^{-\sigma} (1 - \chi) \left(\frac{c_{t+1}}{c_{t+1}^N} \right)^{\frac{1}{\mu}}} \quad (1.8)$$

$$\frac{\lambda_t W_t}{P_t} = \left(c_t - b c_{t-1} - \frac{(h_t)^\omega}{\omega} \right)^{-\sigma} (h_t)^{\omega-1} \quad (1.9)$$

$$R_t^{pol} = R_t^* \mathbb{E}_t \left\{ \frac{S_{t+1}}{S_t \pi_{t+1} (1 - \phi^D (D_t^{*H} + D_t^{*B} - \bar{D}))} \right\} \quad (1.10)$$

where P_t is the aggregate price index, π_t denotes the consumption-based gross inflation rate:

$$P_t = \left[\chi^\mu (P_t^T)^{1-\mu} + (1 - \chi)^\mu (P_t^N)^{1-\mu} \right]^{\frac{1}{1-\mu}}$$

$$\pi_t = \frac{P_t}{P_{t-1}}$$

and P_t^T and P_t^N denote the price of the tradable and non-tradable goods, respectively. Equation (1.8) shows that the optimal relative consumption decision is a function of the real exchange rate. Equation (1.10) is the Uncovered Interest Rate (UIP) parity and states that the interest rate differential is a function of the expected depreciation of the domestic currency.

Non-Tradable Sector

Non-tradable firms are monopolistic competitors who produce a variety of differentiated goods $y_t^N(i)$, where $i \in [0, 1]$, using labor (h_t^N) and capital (k_t^N) as inputs with the following production function:

$$y_t^N(i) = A^N (k_t^N(i))^\alpha (h_t^N(i))^{1-\alpha} \quad (1.11)$$

where A^N denotes the aggregate productivity and $\alpha \in (0, 1)$ is the share of capital on production. Each firm chooses $(P_t^N(i), y_t^N(i))$ to maximize the expected discounted value of profits subject to quadratic adjustment costs in prices and a demand curve for its own variety:

$$\max_{\{P_t^N(i), y_t^N(i)\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta \lambda_t \left[(P_t^N(i) - MC_t^N(i)) y_t^N(i) - \frac{\kappa}{2} \left(\frac{P_t^N(i)}{P_{t-1}^N(i)} - 1 \right)^2 y_t^N \right]$$

subject to:

$$y_t^N(i) = \left(\frac{P_t^N(i)}{P_t^N} \right)^{-\eta} y_t^N$$

$$MC_t^N(i) = \frac{1}{A^N} \left(\frac{\alpha y_t^N(i)}{k_t^N(i)} \right)^\alpha (W_t)^{1-\alpha}$$

where $MC_t^N(i)$ denotes firm's nominal marginal cost, κ denotes the degree of price adjustment costs, η is the elasticity of substitution between non-tradable varieties, and P_t^N and y_t^N denote the average price level and production of non-tradable goods. From the first order condition with respect to $P_t^N(i)$ and under the symmetric equilibrium (i.e. $P_t^N(i) = P_t^N$), we obtain the following expression:

$$\kappa \pi_t^N (\pi_t^N - 1) = \left(\frac{P_t^N - MC_t^N}{P_t} \right) (-\eta) + \frac{P_t^N}{P_t} + \mathbb{E}_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} \pi_{t+1}^N \kappa (\pi_{t+1}^N - 1) \frac{y_{t+1}^N}{y_t^N} \right\} \quad (1.12)$$

where $\pi_t^N = \frac{P_t^N}{P_{t-1}^N}$ denotes the gross inflation rate in the non-tradable sector. Equation (1.12), the New Keynesian Philips curve, denotes the relationship between current inflation, prices, marginal costs, and expected inflation.

The dynamics of capital accumulation in this sector are described by the following expression:

$$k_{t+1}^N = (1 - \delta) k_t^N + i_t^N \left(1 - \frac{\phi^N}{2} \left(\frac{i_t^N}{i_{t-1}^N} - 1 \right)^2 \right) \quad (1.13)$$

where δ is the depreciation rate and the last term denotes the investment adjustment costs.²⁹

Finally, the optimal demand for labor, capital, and investment is given by:

$$(1 - \alpha) \frac{y_t^N}{h_t^N} = \frac{W_t}{P_t^N} \quad (1.14)$$

$$\lambda_t q_t^N = \beta \mathbb{E}_t \left\{ \lambda_{t+1} \left[q_{t+1}^N (1 - \delta) + \alpha \frac{P_{t+1}^N y_{t+1}^N}{P_{t+1}^N k_{t+1}^N} \right] \right\} \quad (1.15)$$

$$\begin{aligned} \lambda_t q_t^N \left[1 - \frac{\phi^N}{2} \left(\frac{i_t^N}{i_{t-1}^N} - 1 \right)^2 - \phi^N \left(\frac{i_t^N}{i_{t-1}^N} \right) \left(\frac{i_t^N}{i_{t-1}^N} - 1 \right) \right] + \\ \beta \mathbb{E}_t \left\{ \lambda_{t+1} q_{t+1}^N \phi^N \left(\frac{i_{t+1}^N}{i_t^N} \right)^2 \left(\frac{i_{t+1}^N}{i_t^N} - 1 \right) \right\} = \lambda_t \frac{P_t^T}{P_t} \end{aligned} \quad (1.16)$$

Tradable Sector

Firms of this sector are price takers both in output and inputs markets. This assumption is motivated by the fact that commodities are the main exports of many emerging economies, for which they take the international reference price. Apart from labor (h_t^T) and capital (k_t^T), these firms also use imported inputs (im_t) for production with the following production function:

$$y_t^T = A^T (k_t^T)^{\gamma_1} (im_t)^{\gamma_2} (h_t^T)^{1-\gamma_1-\gamma_2} \quad (1.17)$$

where A^T denotes the aggregate production and $\gamma_1, \gamma_2 \in (0, 1)$ are the shares of capital and intermediate inputs in production, respectively. The representative firm maximizes the expected discounted profits by choosing inputs and their asset position subject to their production function (1.17), the capital dynamics (1.18), and the working capital constraint (1.19):

$$\max_{\{i_t^T, h_t^T, M_t, D_t^T\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \lambda_t [P_t^T y_t^T - P_t^T i_t^T - W_t h_t^T - P_t^{im} im_t - (M_t - M_{t-1}) + (D_t^T - R_{t-1} D_{t-1}^T)]$$

²⁹Only tradable goods can be invested.

subject to:

$$k_{t+1}^T = (1 - \delta) k_t^T + i_t^T \left(1 - \frac{\phi^T}{2} \left(\frac{i_t^T}{i_{t-1}^T} - 1 \right)^2 \right) \quad (1.18)$$

$$M_t \geq \eta^T [W_t h_t^T + P_t^{im} im_t + P_t^T i_t^T] \quad (1.19)$$

where P_t^{im} is the nominal price of imported inputs, M_t denotes the stock of a non-interest bearing asset, and D_t^T denotes the amount of bank loans. (1.18) describes the capital dynamics in this sector, which is subject to investment adjustment costs. The working capital constraint (1.19) requires firms to hold non-interest rate bearing assets to finance a fraction η^T of their production expenditures every period. Considering that holding non-interest rate bearing assets has an opportunity cost for firms, the working capital constraint holds with equality every time the real interest rate is positive. In order to satisfy this constraint, firms will borrow from banks.

The corresponding optimality conditions of the firm's problem are:

$$(1 - \gamma_1 - \gamma_2) \frac{y_t^T}{h_t^T} = \frac{W_t}{P_t^T} (1 + \eta^T \xi_t) \quad (1.20)$$

$$\gamma_2 \frac{y_t^T}{im_t} = \frac{P_t^{im}}{P_t^T} (1 + \eta^T \xi_t) \quad (1.21)$$

$$\lambda_t q_t^T = \beta \mathbb{E}_t \left\{ \lambda_{t+1} \left[q_{t+1}^T (1 - \delta) + \gamma_1 \frac{P_{t+1}^T y_{t+1}^T}{P_{t+1}^T k_{t+1}^T} \right] \right\} \quad (1.22)$$

$$\begin{aligned} & \lambda_t q_t^T \left[1 - \frac{\phi^T}{2} \left(\frac{i_t^T}{i_{t-1}^T} - 1 \right)^2 - \phi^T \left(\frac{i_t^T}{i_{t-1}^T} \right) \left(\frac{i_t^T}{i_{t-1}^T} - 1 \right) \right] + \\ & \beta \mathbb{E}_t \left\{ \lambda_{t+1} q_{t+1}^T \phi^T \left(\frac{i_{t+1}^T}{i_t^T} \right)^2 \left(\frac{i_{t+1}^T}{i_t^T} - 1 \right) \right\} = \lambda_t \frac{P_t^T}{P_t} (1 + \eta^T \xi_t) \end{aligned} \quad (1.23)$$

$$\xi_t = \lambda_t - \mathbb{E} \left\{ \frac{\beta \lambda_{t+1}}{\pi_{t+1}} \right\}$$

$$\mathbb{E}_t \left(\beta \frac{\lambda_{t+1}}{\pi_{t+1}} R_t \right) = \lambda_t$$

From the last two expressions, the multiplier of the working capital constraint (ξ_t) is:

$$\xi_t = \frac{R_t - \pi_{t+1}}{R_t} \quad (1.24)$$

The working capital constraint induces a wedge between the marginal product and marginal cost of labor, imported inputs, and investment demand (equations (1.20), (1.21), and (1.23), respectively). This wedge is increasing with the interest rate at which firms can borrow (R_t) and with the intensity of the constraint (η^T).

Banks

Financial intermediaries lend funds to tradable firms using their net worth and borrowing from abroad in the form of one-period non-contingent debt denominated in foreign currency.³⁰ Each banker manages a bank until retirement, when net worth is distributed back to households as dividends. As in [Gertler and Kiyotaki \(2010\)](#) and [Gertler and Karadi \(2011\)](#), this assumption limits the possibility that banks may accumulate earnings to avoid financial constraints. In this context, the bank's balance sheet is defined as:

$$D_t = N_t + S_t D_t^{B*} \quad (1.25)$$

where D_t is the amount of total loans, N_t denotes the net worth of the bank at period t , and D_t^{B*} denotes the amount of foreign debt.

At the beginning of each period, banks can choose to operate honestly or to divert assets for personal use. This problem introduces an incentive compatibility constraint that limits the amount of debt they issue to a multiple $(\theta^B - 1)$ of their net worth N_t . Combining this constraint with the balance sheet equation (1.25), the incentive compatibility constraint becomes:

$$D_t \leq \theta^B N_t \quad (1.26)$$

The banker exits the financial sector with an exogenous probability $\sigma^B \in (0, 1)$. In this case, the banker transfers the accumulated net worth to the households. Every period, households transfer to new bankers a fraction of the assets of exiting bankers. In particular, I assume that the net worth of the new bankers (N_t^N) is given by the following expression:

$$N_t^N = (1 - \sigma^B) \frac{v^B}{(1 - \sigma^B)} D_{t-1}$$

where $\frac{v^B}{(1 - \sigma^B)}$ denotes the transferred fraction. Then, aggregate net worth is composed by the one of existing and new bankers' net. Thus, the aggregate evolution of bank's net worth is:

³⁰As discussed before, non-tradable firms do not have any reason to demand credit.

$$N_t = \sigma^B \left\{ \frac{R_{t-1}D_{t-1}}{\pi_t} - \frac{S_t R_{t-1}^* D_{t-1}^{B*}}{P_t \pi_t} \right\} + v^B D_{t-1} \quad (1.27)$$

The net worth dynamics depends positively on the interest rate differential between loans and external liabilities.

Market Clearing Conditions and Exogenous Processes

Non-tradable output can be either consumed domestically or used to pay the costs of changing prices:

$$y_t^N = c_t^N + \frac{\kappa}{2} (\pi_t^N - 1)^2 y_t^N \quad (1.28)$$

The balance of payments and the trade balance are equal to:

$$tb_t - \left(\frac{R_{t-1}^*}{\pi_t} - 1 \right) (D_{t-1}^{H*} + D_{t-1}^{B*}) = (D_t^{H*} + D_t^{B*}) - (D_{t-1}^{H*} + D_{t-1}^{B*}) \quad (1.29)$$

$$tb_t = y_t - c_t^T - i_t^T - i_t^N - \frac{P_t^{im}}{S_t} im_t - \frac{\phi^D}{2} (D_t^{H*} + D_t^{B*} - \bar{D})^2 \quad (1.30)$$

Additionally, the labor and credit markets have to clear:

$$h_t = h_t^N + h_t^T \quad (1.31)$$

$$D_t = D_t^T \quad (1.32)$$

Considering the variables used in the empirical analysis, I define the real exchange rate ($reer_t$) and the terms of trade (p_t^{CM}) as follows:

$$reer_t = \frac{P_t}{S_t P_t^{T*}} = \frac{P_t}{S_t} \quad (1.33)$$

$$P_t^{im} = \frac{P_t^T}{tot_t} \quad (1.34)$$

In order to close the model, I need to assume a process for the international interest rate and for the terms of trade faced by the economy. Considering that I want to assess the transmission of the interest rate shocks to the emerging economy, I follow [Uribe and Yue \(2006\)](#) and use the estimated processes from Section 1.3.3. In particular, the process for the international interest rate is described by:

$$R_t^* = R_t^{US} + \hat{F} \left(d_{t-j}, \text{tot}_{t-j}, \text{gdp}_{t-j}, i_{t-j}, \frac{tb_{t-j}}{\text{gdp}_{t-j}}, \text{reer}_{t-j}, R_{t-j}^* \right) \quad \forall j = 0, 1, 2 \quad (1.35)$$

$$R_t^{US} = R_{ss}^{US} + \sum_{s=1}^2 \hat{\rho}_s^R R_{t-s}^{US} + \Delta i_t^u + \sum_{j=0}^2 \Delta i_{t-j,t}^a$$

where R_t^{US} denotes the current U.S. interest rate, $\text{gdp}_t = \frac{P_{ss}^T y_{ss}^T + P_{ss}^N y_{ss}^N}{P_{ss}}$, and the second term of the first expression is the country spread, which is defined as the difference in interest rate with respect to the safe asset. Following the VAR specification, the sovereign spread depends on the current state and past values of the main macroeconomic variables of the country. I also introduce the estimated equation that determines the terms of trade dynamics:

$$\text{tot}_t = \text{tot}_{ss} + \sum_{s=1}^2 \rho_s^t \text{tot}_{t-s} + \zeta_0 \Delta i_t^u + \sum_{s=0}^2 \zeta_{s+1} \Delta i_{t-s,t}^a \quad (1.36)$$

where the last two terms reflect the effect that anticipated and unanticipated U.S. interest rate shocks have on the terms of trade dynamics.³¹ Finally, I assume that the domestic policy rate is determined following a Taylor rule as follows:

$$i_t = i + \omega_\pi (\pi_t - 1) \quad (1.37)$$

Then, the U.S interest rate shocks are the only source of exogenous fluctuations in this economy.

Equilibrium

The equilibrium is described by the system of non-linear equations (1.6)-(1.37). Considering that this system cannot be solved analytically, I simulate the model using a first order approximation around the deterministic steady state when bank's incentive compatibility constraint is always binding. Appendix A.6 displays all the conditions to compute the steady state.

³¹In the Empirical Analysis, I also allow the terms of trade to react to domestic macroeconomic conditions of emerging economies. However, the individual coefficients are not statistically significant.

1.4.2 Calibration

I calibrate the model to match some empirical moments of emerging economies and following standard values in the literature. Table 1.6 displays the value for each parameter. Following [Mendoza \(1991\)](#) and [Uribe and Yue \(2006\)](#), I set the intertemporal elasticity of substitution σ equal to 2 and the parameter ω that determines curvature of the labor supply to 1.455.³² I set the value of the steady state quarterly interest rate faced by the small open economy in international financial markets to 2% annual, which implies an annualized rate of 8.24%. This rate is consistent with the mean interest rate of the sample used in the VAR (8.19%) and implies that β is equal to 0.9804. Following [Uribe and Yue \(2006\)](#), I set the steady state level of debt \bar{d} to induce a 1% trade balance to GDP ratio in steady state. The value of the depreciation rate δ is set to 2.5%, a standard value in the real business cycle literature. Regarding the production functions, I set the capital share in tradable sector γ_1 and in the non-tradable one α to 0.25 and 0.3, respectively, and γ_2 to 0.1. These values implies that the labor share of income is 65% in the tradable sector and 70% in the non-tradable one. I set the elasticity of substitution between tradable and non-tradable goods μ to 0.5, in line with the empirical estimates surveyed by [Akinci \(2011\)](#). I calibrate χ to 0.35 such that non-tradable consumption goods represent around 50% of total consumption in steady state.

The parameters that determine the price adjustment costs and the mark-ups are calibrated following the literature. In particular, I set the elasticity of substitution among non-tradable varieties η to 11, which implies that the steady state mark up over the marginal cost is 10%. I calibrate the parameter that determines the price adjustment costs κ to 19.62 such that the fraction of firms that adjust prices is 50%.³³

To calibrate the parameters of the banking sector, I follow the values used by [Aoki, Benigno, and Kiyotaki \(2016\)](#) and [Shousha \(2016\)](#). In particular, I set the exogenous probability of continuing active as a banker σ^B to 0.945 and v^B to 1% to make new bankers start with a small net worth. I set θ^B to 1.05, which implies that banks can issue foreign debt up to 105% of their net worth.

Finally, following [Uribe and Yue \(2006\)](#), I calibrate the capital constraint requirement η^T , the investment adjustment costs of both sectors $\{\phi^N, \phi^T\}$, the internal habit formation parameter b , and the parameter that determines the debt adjustment costs η^D to minimize the distance between the empirical IRFs and the theoretical counterpart. The value of $\eta^T = 2.1$ implies that firms hold a level of working capital constraint equivalent to 6 months

³²The labor supply elasticity implied by this value is $2.2 (= 1/(\omega - 1))$

³³In the theoretical model, κ is related to the fraction of firms that do not adjust their prices f through the following expression: $\kappa = \frac{(\eta-1)f}{(1-f)(1-\beta f)}$

of inputs expenditure. The implied investment adjustment costs are set to 3 for both sectors to match the persistence of the investment response to both shocks. Finally, the value of the debt adjustment costs is key to match the volatility of the trade balance to GDP ratio.

1.4.3 Impulse Responses

In this section, I compare the predictions of the theoretical model to the empirical ones (Figures 1.2 and 1.3). In particular, I simulate 1,000 data points from the theoretical model and use this artificial data set to estimate the VAR described in Section 1.3.1. Figure 1.6 displays the responses to a two quarters ahead anticipated 25 basis points contractionary U.S. interest rate shock.³⁴

In response to a contractionary shock, banks suffer a deterioration of their balance sheet due to the exchange rate depreciation. This change in relative prices restricts both the amount of debt they can issue in international markets and the supply of domestic credit. Although the change in relative prices fosters a transfer of resources to the tradable sector, its production falls because the working capital constraint is affected by the increase in the lending interest rate. The observed decrease in GDP is also explained by the fall in non-tradable output. Finally, the trade balance to GDP ratio increases by a 0.8% point only when the U.S. interest rate increases, slightly bigger than the empirical findings. Overall, the model also induces responses that are stronger before the change in the U.S. interest rate. Figure 1.7 displays the IRFs to an unanticipated 25 basis points contractionary U.S. interest rate shock.

This shock increases the rate at which the domestic economy can get international loans by 0.5% points on impact and induces a depreciation of the exchange rate. As in the case of the anticipated shock, these movements affect banks' balance sheets and limit their access to international capital markets. Thus, banks tighten their supply of domestic credit, affecting negatively the production and investment decisions of the tradable sector. In this context, the trade balance to GDP ratio also increases by a 0.4% point.

Overall, the theoretical model matches well the empirical responses for most of the variables to anticipated and unanticipated U.S. interest rate shocks. The main differences between the empirical and theoretical results are the responses of the real exchange rate and GDP to the unanticipated shock. Although the IRFs of both variables are qualitatively similar to the empirical counterparts, both of them are milder. Finally, the theoretical response of cross-border bank flows to the anticipated shock is a bit more delayed than in the data.

³⁴Considering that in the theoretical model I normalize all the prices with respect to the CPI, in this figure I compare the responses of the Real Exchange, which includes the evolution of domestic prices and nominal exchange rate, instead of the ones of Nominal Exchange Rate and CPI.

1.4.4 Sensitivity of Impulse Responses

Previous results rely on the calibration described in Section 1.4.2. However, there is an intrinsic uncertainty about the values of some calibrated parameters that may explain the theoretical dynamics. For example, [Akinci \(2011\)](#) surveys different works that estimate the atemporal elasticity of substitution between tradable and non-tradable goods (μ) and shows that estimates lie between $[0.43, 0.74]$. This parameter is key not only for consumption dynamics but also for other macroeconomic variables.

To assess the robustness of the theoretical results, let θ^p be a vector of parameters whose value is uncertain. Following [Pappa \(2009\)](#), I assume that θ^p is uniformly distributed over Θ^p , where $\Theta^p = \prod_{i=1}^I \Theta_i^p$ is the set of admissible parameter values and Θ_i^p is an interval for each parameter i . I generate 1,000 draws for $\theta_i^{p,l}$ from Θ_i^p , compute the corresponding IRFs for each draw. Finally, I plot the 5 and 95 percentiles of the simulated distribution of IRFs.

Some parameters of the model are held fixed since they are standard in the literature or in order to avoid indeterminacy. The intervals of the remaining parameters are set according to previous papers and to consider a broad range of cases. Table 1.7 displays the intervals for each of them. Figures 1.8 and 1.9 display the IRFs to an anticipated shock and unanticipated U.S. interest rate shock.

The responses of all the variables to both shocks are robust to different parametrizations. The decline in cross-border bank flows, GDP, and Investment is significant if I consider the 90% probability bands from the simulated draws. Then, the effects of both shocks do not rely on a particular parametrization.

1.4.5 Transmission Channels

In this subsection, I analyze the role of financial frictions in the transmission of both shocks. One advantage of the theoretical model is that I can assess how the different frictions affect the response of macroeconomic variables. The model considers the following financial frictions: the incentive compatibility constraint, currency mismatch between bank's assets and liabilities, working capital constraint, and the dynamics of the country interest rate. The key frictions to explain the observed dynamics are the interaction between the working capital constraint and the sovereign spread.³⁵ In particular, I reduce the working capital constraint intensity from $\eta^T = 2.1$ to $\eta^T = 1.05$. Thus, with this new parametrization, firms need to hold less non-interest rate bearing assets for the same production plan. Additionally, I remove the feedback from domestic macroeconomic conditions to the country interest rate, which implies that countries can borrow at the international interest rate.

³⁵The other financial frictions do not affect the results significantly.

Figure 1.10 displays the IRFs to an anticipated shock when the country spread is zero and $\eta^T = 1.05$.

The country spread and the working capital constraint explain around 34% and 54% of GDP and investment dynamics, respectively. This change in response is partially due to the lower decline in cross border bank flows, the lower depreciation of the real exchange rate, and the different dynamics of the country interest rate. Finally, the trade balance is also less volatile when there is no country spread and the working capital constraint intensity is reduced. Figure 1.11 displays the IRFs to an unanticipated shock when the country spread is zero and $\eta^T = 1.05$.

Sovereign spread and the working capital constraint also explain around 35% and 55% of GDP and investment dynamics in case of an unanticipated shock. They also explain a significant fraction of the trade balance and cross border bank flows dynamics. The relevance of the sovereign spread to explain the transmission of interest rate shocks is in line with the findings of [Uribe and Yue \(2006\)](#). These results are also similar to the ones of [Shousha \(2016\)](#), who analyzes the transmission of commodity price shocks to emerging economies.

1.5 Conclusions

This paper has explored the role of anticipation in assessing the effects of U.S. interest rate shocks on emerging economics. Anticipation accounts for 80% of the effective quarterly fluctuations in the Fed Funds and 47% of the narrative series of monetary policy shocks. Three major conclusions can be derived from the analysis. First, monetary news generate an immediate reaction of macroeconomic variables, even before the change in the U.S. interest rate materializes. In particular, an anticipated 25 basis points increase in the U.S. Fed Funds rate generates an immediate 0.5% decrease in GDP and 1.3% fall in investment from their trends. Second, unanticipated contractionary U.S. interest rate shocks induce a comparable contraction of economic activity to anticipated ones but after the actual change in the rate. Finally, the financial channel, via cross border bank flows and country interest rate, is important for the transmission of both shocks while terms of trade do not display a statistically significant reaction. Results are robust to alternative specifications (for example, controlling for global conditions), samples, and across different exchange rate regimes.

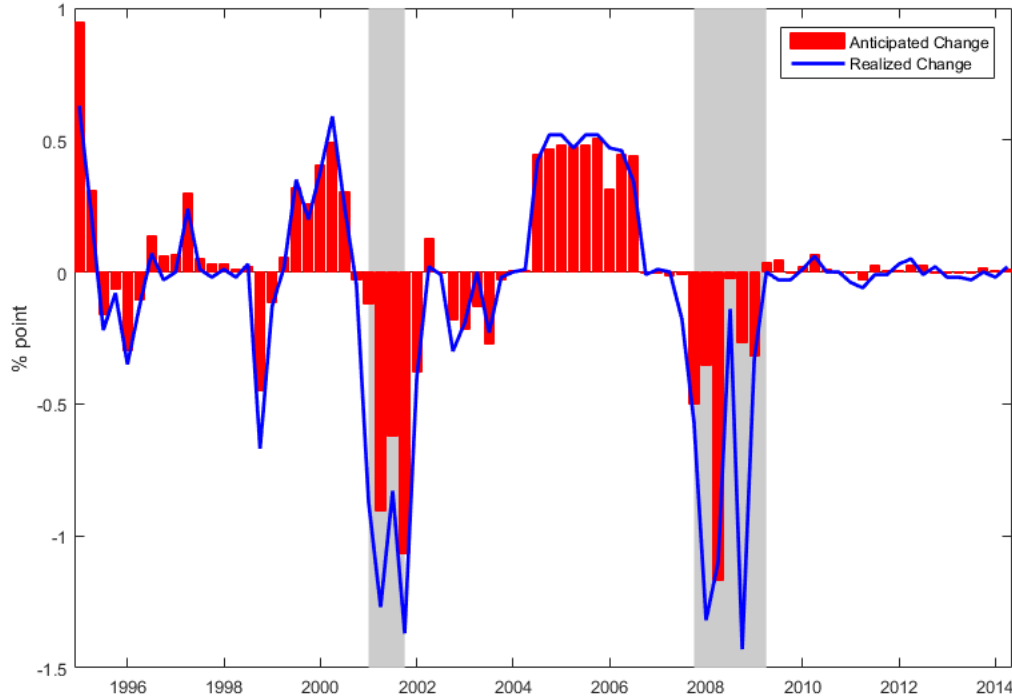
In order to characterize the transmission of U.S. interest rate shocks to emerging economies, I develop a small open economy model with a banking sector. The model features

two key financial frictions to explain the observed dynamics. First, a working capital constraint that states that firms have to hold a fraction of current expenditures in non-interest rate bearing assets (see [Neumeyer and Perri \(2005\)](#) and [Uribe and Yue \(2006\)](#)). Second, I include the estimated feedback from domestic macroeconomic variables to the country interest rate. In this framework, I show that the working capital constraint and the sovereign spread explain a significant fraction of the macroeconomic adjustment to anticipated and unanticipated U.S. interest rate shocks.

Results show that anticipation is crucial for assessing the effects of U.S. interest rate shocks, since a significant part of the adjustment in emerging economies takes place before a change in the interest rate occurs. These findings help in understanding the adjustment of these economies to the current FED's liftoff. From a policy perspective, movements in the international interest rate pose a significant trade-off to emerging economies. On the one hand, they induce pressures to tight monetary policy in order to avoid large currency depreciations that may affect the banking sector. On the other hand, they create incentives to lower the interest rate to boost economic activity. The theoretical model developed in this paper can be used to determine the optimal policy to counteract the effects of these shocks. [Aoki, Benigno, and Kiyotaki \(2016\)](#) show that macroprudential policies are complementary to an inflation targeting regime to enhance welfare but that inflation targeting alone can reduce welfare. However, their theoretical framework considers only a production sector subject to sticky prices, disregards the anticipation effects of interest rate shocks, and does not include the main financial channels identified in this paper. All of these facts are important to explain the observed dynamics. Thus, it would be interesting to study optimal policy in this framework considering a policy rule that reacts not only to inflation and real exchange rate but potentially also to expected and current foreign interest rate. This topic constitutes a promising opportunity for future research.

1.6 Figures and Tables

Figure 1.1: Anticipated and realized changes in the Fed Funds Rate



Note: Anticipated Change is computed as difference between market expectations regarding the value of the Fed Funds rate in the current quarter and the realized value of the previous quarter. The realized change denotes the change in the average Fed Funds rate with respect to the previous quarter. Shaded areas denote the recessions in the U.S defined by NBER.

Table 1.1: Horizon of forecastability of changes in the Fed Funds

	Δi_t			
	$\Delta i_{t,0}^a$	$\Delta i_{t-1,1}^a$	$\Delta i_{t-1,1}^a$	$\Delta i_{t-3,3}^a$
Adj. R^2	0.80	0.31	0.11	0.01
F-Stat	308.1	33.8	9.4	0.1

Note: OLS estimates of the projection of Δi_t on the expected change in the interest rate ($\Delta i_{t,j}$). Δi_t denotes the contemporaneous change in the Fed Funds rate. $\Delta i_{t,j}^a$ denotes the expected change in the interest rate for j quarters ahead with respect to the previous one, conditional on the information available at the beginning of time t . R^2 and F – Stat correspond to the adjusted R-squared and the value of the F statistic, respectively.

Table 1.2: Correlation across different shocks

Series	TT(2016)	Δi_t^u	$\Delta i_{t,0}^a$	$\Delta i_{t-1,1}^a$	$\Delta i_{t-2,2}^a$
Δi_t^u	0.51***				
$\Delta i_{t,0}^a$	0.69***	0.08			
$\Delta i_{t-1,1}^a$	0.50***	0.16	0.59***		
$\Delta i_{t-2,2}^a$	0.21	0.12	0.29***	0.55***	

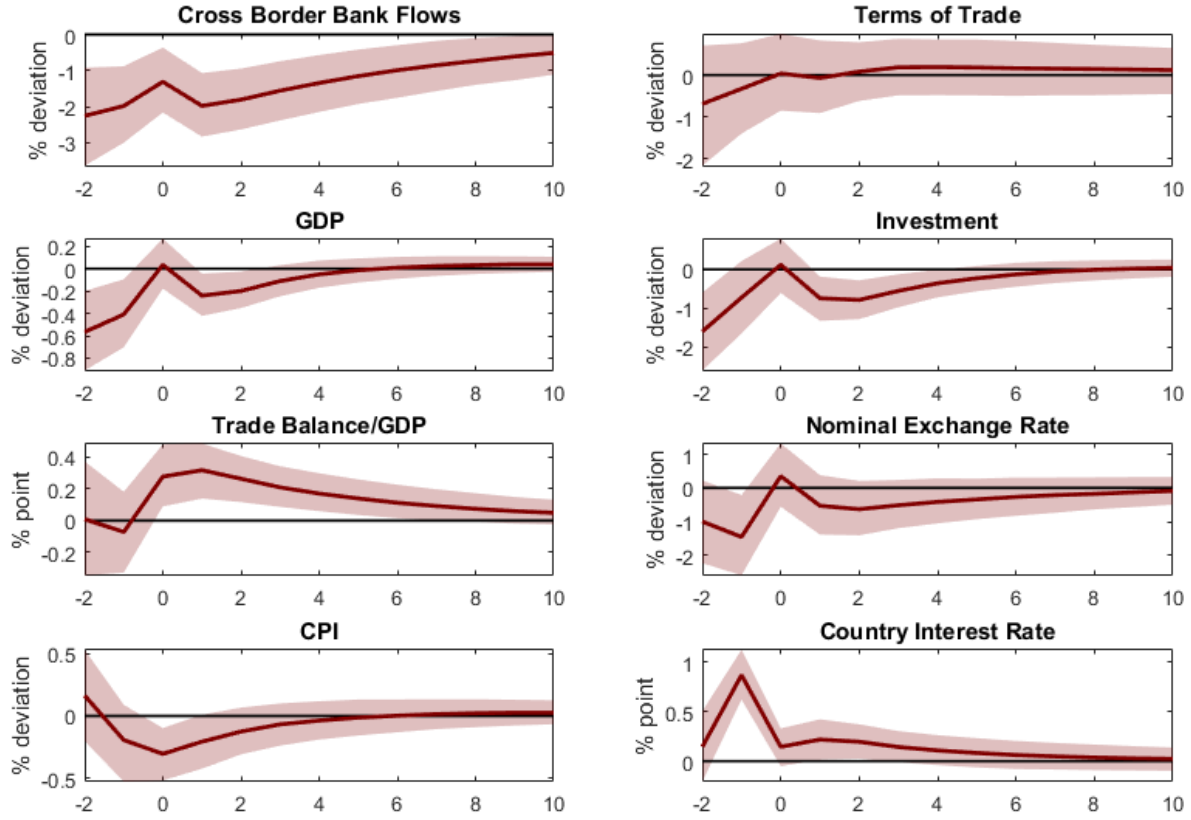
Note: Contemporaneous correlation between the different shocks and their significance levels. ***, **, and * denote 1%, 5% and 10% confidence level. TT(2016) denotes the monetary policy shocks series of [Tenreiro and Thwaites \(2016\)](#), who update the series of [Romer and Romer \(2004\)](#). $\Delta i_{i,j}^a$ denotes the anticipated U.S. interest rate shock for j quarters ahead with respect to the previous one, conditional on the information available at the beginning of time t . Δi_j^u is the unanticipated U.S. interest rate shock.

Table 1.3: Predictive power of anticipated shocks

	TT(2016)	TT(2016)	TT(2016)	TT(2016)
$\Delta i_{t,0}^a$	0.73*** (0.11)			0.55*** (0.15)
$\Delta i_{t-1,1}^a$		0.53*** (0.13)		0.32* (0.18)
$\Delta i_{t-2,2}^a$			0.40 (0.27)	-0.13 (0.25)
Adj. R^2	0.47	0.24	0.02	0.42
F-Stat	45.74***	16.54***	2.23	12.96***
Obs	52	51	50	50

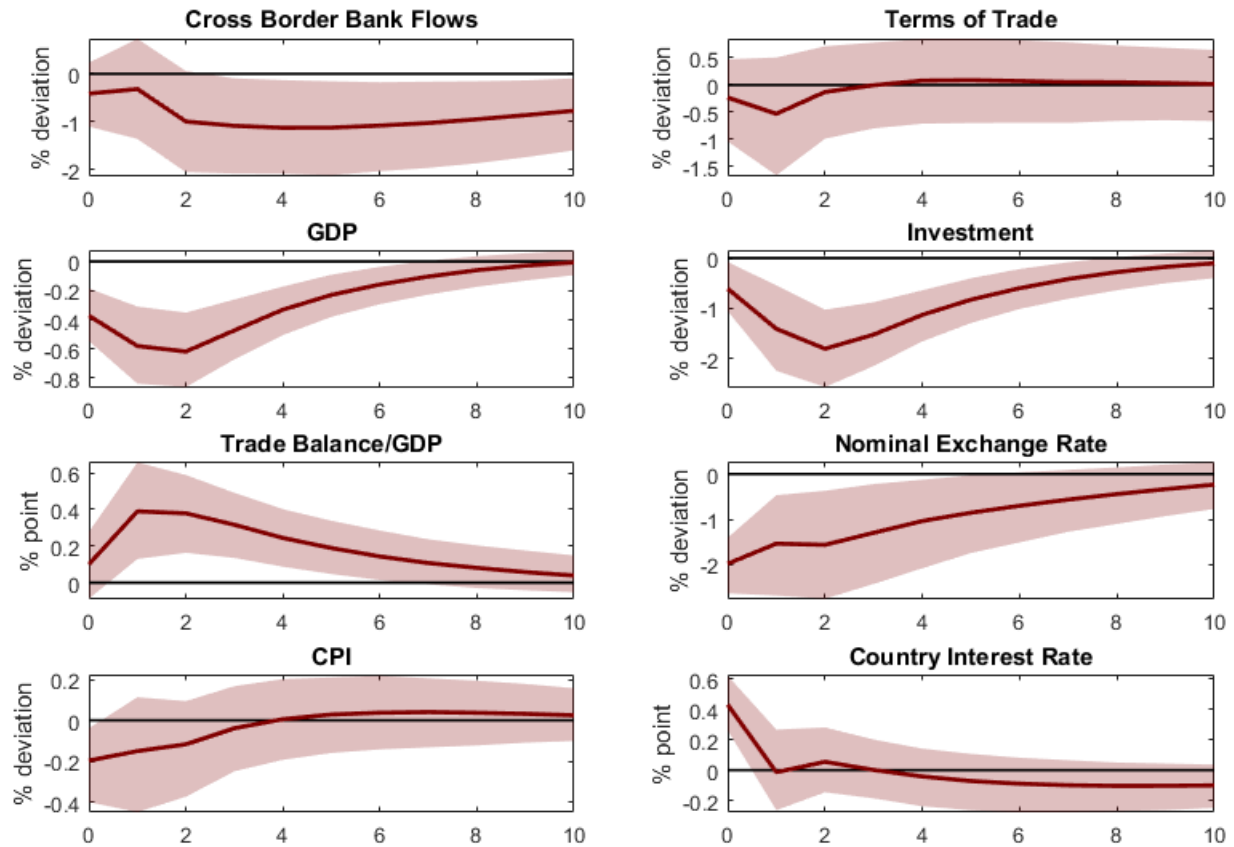
Note: OLS regressions between the different shocks. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively. TT(2016) denotes the monetary policy shocks series of [Tenreiro and Thwaites \(2016\)](#), who update the series of [Romer and Romer \(2004\)](#). $\Delta i_{i,j}^a$ denotes the anticipated U.S. interest rate shock for j quarters ahead with respect to the previous one, conditional on the information available at the beginning of time t . Adj. R^2 and F-Stat correspond to the adjusted R-squared and the value of the F statistic.

Figure 1.2: IRFs to a 2 quarters ahead anticipated 25bp contractionary U.S. interest rate shock



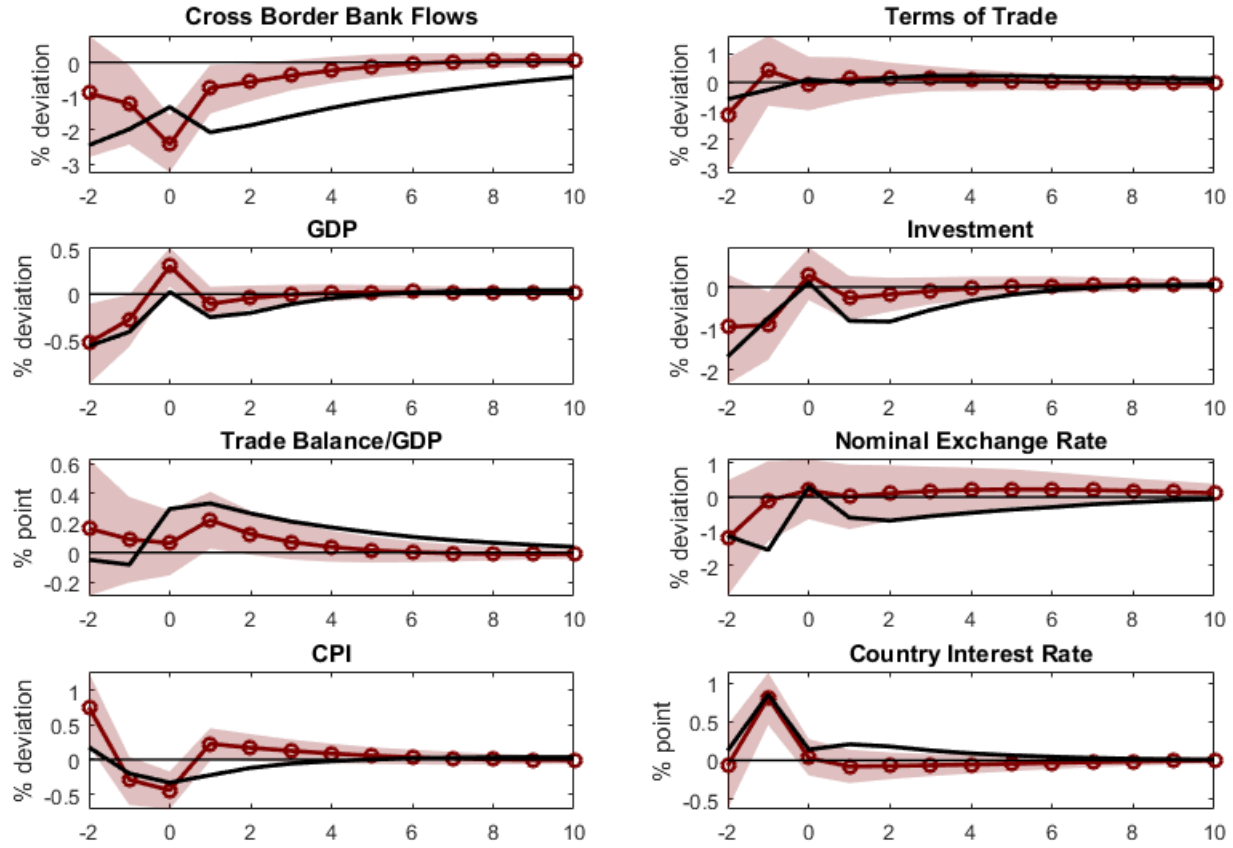
Note: Solid lines denote point estimates of impulse responses from the VAR system (1.5); 90% confidence bands are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. $t = 0$ denotes the period when the U.S. interest rate increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Confidence bands are computed through 1,000 bootstrap replications. Horizon is in quarters.

Figure 1.3: IRFs to an unanticipated 25bp contractionary U.S. interest rate shock



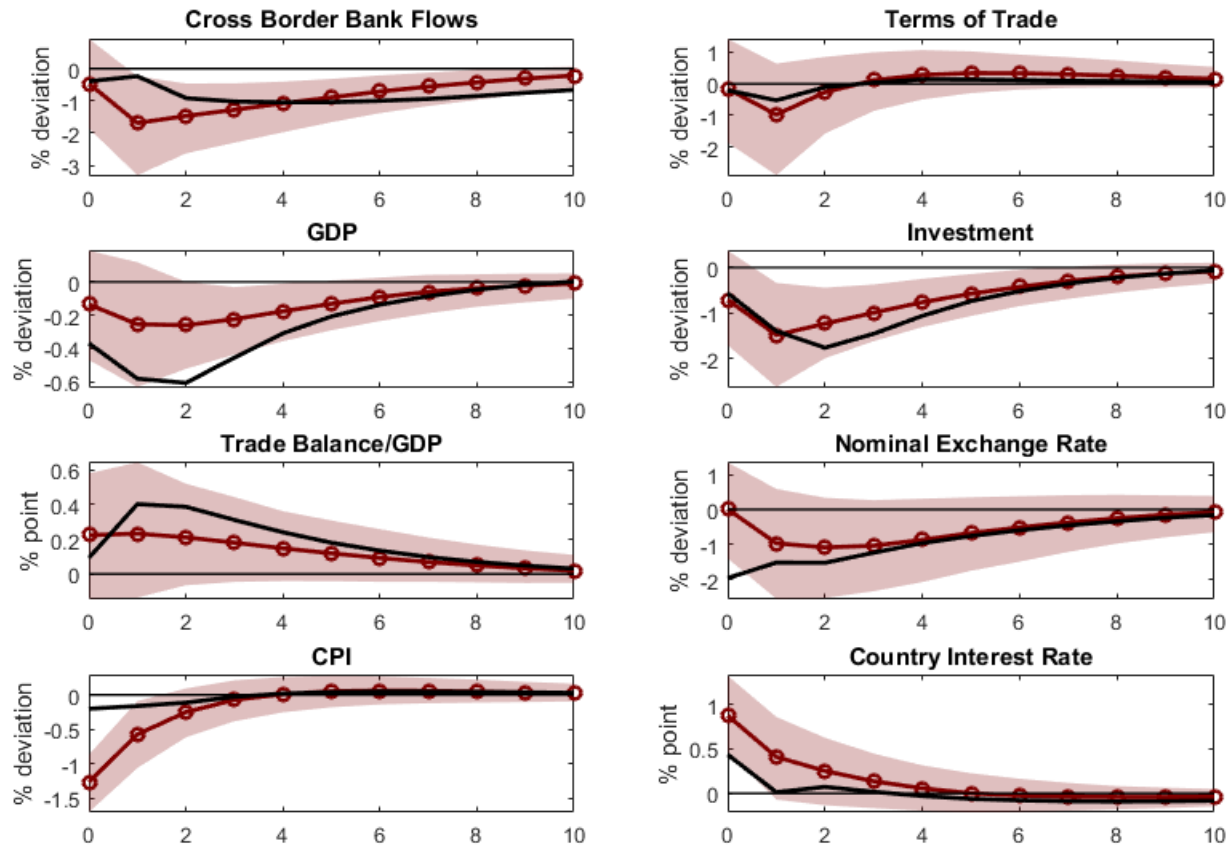
Note: Solid lines denote point estimates of impulse responses from the VAR system (1.5); 90% confidence bands are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. Confidence bands are computed through 1,000 bootstrap replications. Horizon is in quarters.

Figure 1.4: IRFs to 2 quarters ahead anticipated 25bp contractionary U.S. interest rate shock 1995-2007



Note: Solid and circled sign lines denote the point estimate of impulse responses for emerging economies from the VAR system (1.5) using full sample and pre-crisis (1995-2007) sample, respectively. 90% confidence bands for pre-crisis are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Confidence bands are computed through 1,000 bootstrap replications.

Figure 1.5: IRFs to unanticipated 25bp contractionary U.S. interest rate shock 1995-2007



Note: Solid and circled sign lines denote the point estimate of impulse responses for emerging economies from the VAR system (1.5) using full sample and pre-crisis (1995-2007) sample, respectively. 90% confidence bands for pre-crisis are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. Confidence bands are computed through 1,000 bootstrap replications. Horizon is in quarters.

Table 1.4: Five quarters cumulative response to an anticipated 25bp contractionary U.S. interest rate shock

	Baseline	Alt Shock	Fin Cond	GFC	WGDP	VIX	15 Coun	Fixed FX
Credit	-9.8 ^a	-10.2 ^a	-8.7 ^a	-8.9 ^a	-9.6 ^a	-9.3 ^a	-3.6 ^b	-9.9 ^a
TOT	-0.7	-1.1	-0.8	-0.6	-0.7	-0.4	-1.4	-1.3
GDP	-1.5 ^a	-2.0 ^a	-1.2 ^a	-1.1 ^a	-1.3 ^a	-1.3 ^a	-1.0 ^a	-1.5 ^b
I	-4.1 ^a	-5.1 ^a	-3.2 ^b	-2.9 ^b	-3.7 ^b	-3.8 ^b	-2.5 ^b	-4.1 ^b
TB	0.8 ^b	0.8 ^b	0.8 ^b	0.8 ^b	0.8 ^b	0.7 ^b	-0.3	-1.3 ^b
NEER	-3.8 ^b	-5.1 ^b	-3.1 ^b	-3.1 ^b	-3.6 ^b	-2.9	-1.6 ^b	0.6
CPI	-0.7	-0.7	-0.6	-0.7	-0.7	-0.8 ^b	-0.1	2.3
R	1.5 ^a	1.7 ^a	1.6 ^a	1.6 ^a	1.5 ^a	1.4 ^a	1.1 ^a	0.9

Note: Cumulative five quarters responses to a 2 quarters ahead anticipated 25 basis points (one standard deviation) contractionary U.S. interest rate shock. *a* and *b* denote statistical significance at 90% and 68%, respectively. The five quarters cumulative response to an anticipated shock denotes the sum of the responses between periods -2 and 2. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). All responses are expressed in %. Confidence bands are computed through 1,000 bootstrap replications.

Table 1.5: Five quarters cumulative response to an unanticipated 25bp contractionary U.S. interest rate shock

	Baseline	Alt Shock	Fin Cond	GFC	WGDP	VIX	15 Coun	Fixed FX
Credit	-3.0 ^b	-2.3	0.2	-2.0	-1.1	-1.4	-1.3	-0.8
TOT	-0.7	-2.5 ^b	-0.6	-0.7	-0.1	-0.3	-1.8 ^b	-6.1 ^b
GDP	-2.0 ^a	-1.8 ^a	-0.4	-1.1 ^a	-1.2 ^a	-1.5 ^a	-1.4 ^a	-0.2
I	-5.4 ^a	-3.6 ^a	-2.0	-3.3 ^a	-3.8 ^a	-4.6 ^a	-2.6 ^a	0.1
TB	1.6 ^a	1.4 ^a	1.7 ^a	1.5 ^a	1.6 ^a	1.5 ^a	0.9 ^b	0.7
NEER	-7.1 ^a	-6.5 ^a	-4.2 ^b	-5.4 ^a	-6.3 ^a	-4.4 ^a	-4.7 ^a	-0.7
CPI	-0.6	-0.8 ^b	-0.7	-0.5	-0.7 ^b	-0.8 ^b	-0.0	-1.9 ^b
R	1.0 ^b	0.9 ^b	1.3 ^a	0.7 ^b	0.9 ^b	0.6 ^b	2.2 ^a	5.7 ^a

Note: Cumulative five quarters response to an unanticipated 25 basis points (one standard deviation) contractionary U.S. interest rate shock. *a* and *b* denote statistical significance at 90% and 68%, respectively. The five quarters cumulative response to an unanticipated shock denotes the sum of the responses between periods 0 and 4. All responses are expressed in %. Confidence bands are computed through 1,000 bootstrap replications.

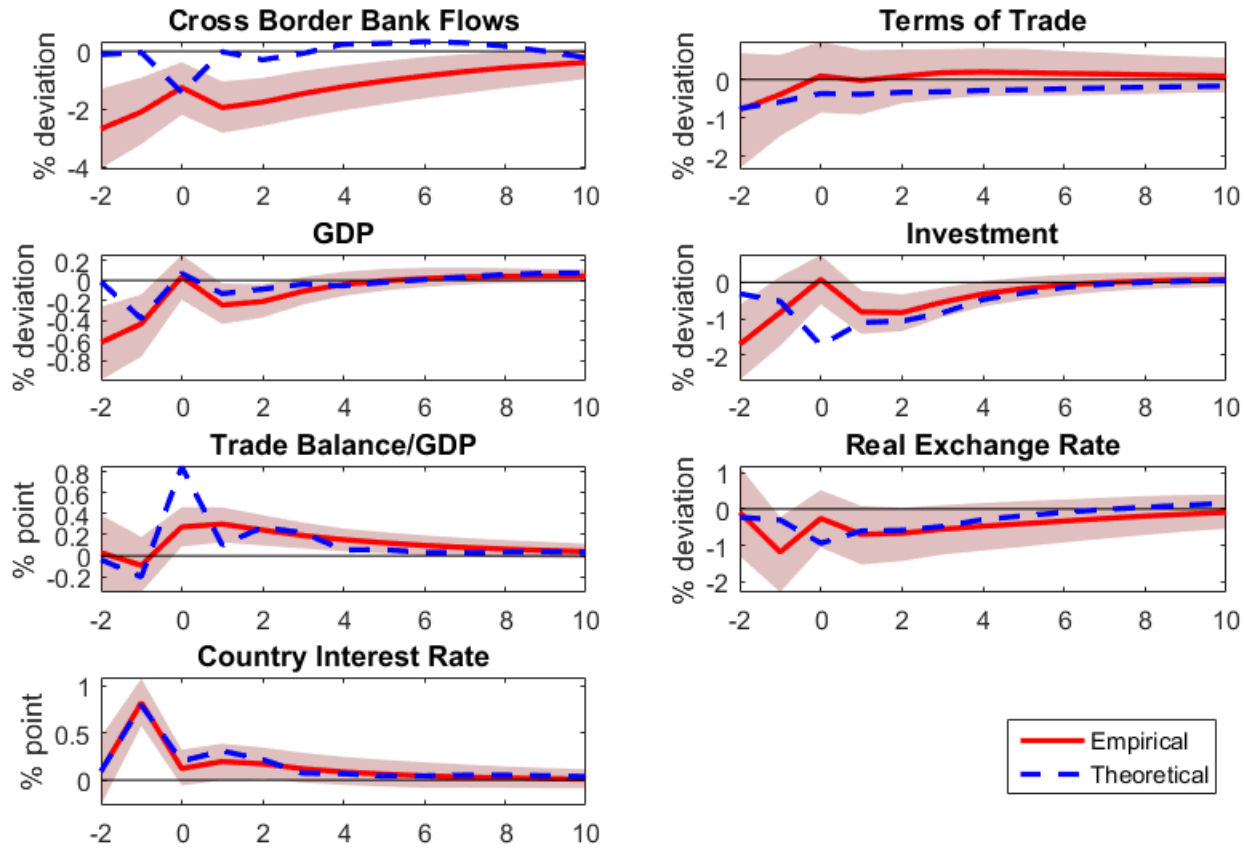
Table 1.7: Parameter Ranges

Parameter		Range	Note
Labor supply curvature	ω	[1.4,2]	Labor supply elast. between [1, 2.5]
Elast. of subst. $\{c^T, c^N\}$	μ	[0.43,0.74]	Range of estimates surveyed by Akinci (2011)
Weight of c^T on c	χ	[0.32,0.42]	$0.5 \leq \frac{p^N c^N}{c} \leq 0.6$
Price adjustment cost	κ	[19,56]	Proportion of non-adjusters btw. [0.5, 0.66]
Fraction of working capital const.	η^T	[1.5,2.5]	Values around 2.1
Debj adj. costs	ϕ^D	[8,12]	Values around 10
Investment adj. costs in T	ϕ^T	[3,5]	Values around 3
Investment adj. costs in N	ϕ^N	[3,5]	Values around 3
Taylor rule inflation coefficient	ω^π	[1.1,3]	Values around 1.5

Table 1.6: Calibrated Parameters

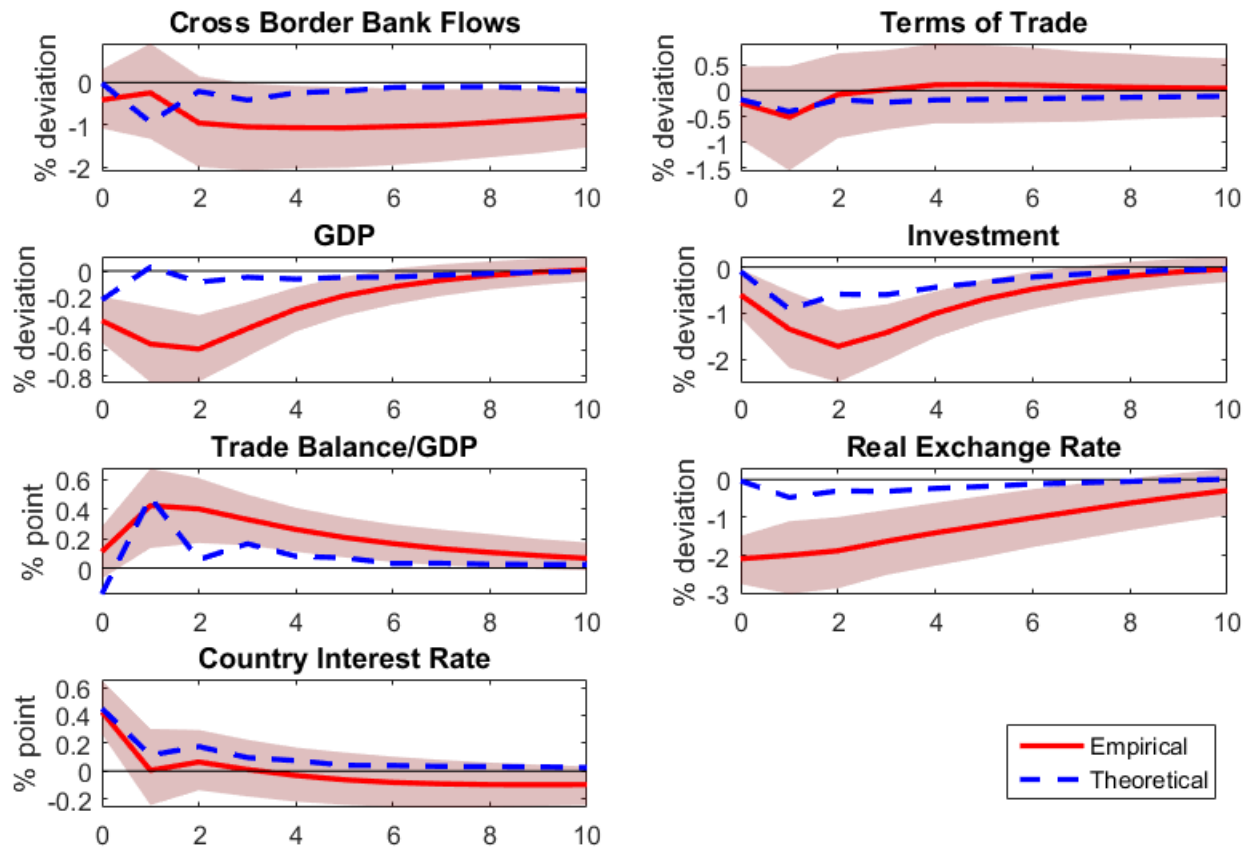
Parameter		Value	Target/Source
U.S. interest rate	R_{ss}^*	1.02	Sample mean
Discount factor	β	0.9804	$\beta = 1/R_{ss}^*$
Steady state foreign debt	\bar{d}	0.2	$S_{ss}tb_{ss}/gdp_{ss} = 0.01$
Depreciation rate	δ	0.025	Standard value
Intertemporal elast. of subs.	σ	2	Standard value
Habit formation parameter	b	0.1	Standard value
Labor supply curvature	ω	1.455	Labor supply elasticity=2.2
Elast. of subst. $\{c^T, c^N\}$	μ	0.5	Akinci (2011)
Weight of c^T on c	χ	0.35	$p_{ss}^N c_{ss}^N / c_{ss} = 0.5$
Share of capital in T	γ^1	0.25	Capital share of income=25%
Share of imported inputs in T	γ^2	0.1	Inputs share of income=10%
Share of capital in sector N	α	0.3	Capital share of income=30%
Elast. of subs. btw. N varieties	η	11	Mark-up non-tradable=10%
Price adjustment cost	κ	19.62	50% of firms do not adjust prices
Bank's continuation probability	σ^B	0.945	Aoki, Benigno, and Kiyotaki (2016)
Transfer rate to new banks	v^B	0.01	Shousha (2016)
Bank's borrowing limit	θ^B	1.05	Match IRFs
Fraction of working capital const.	η^T	2.1	Match IRFs
Debj adj. costs	ϕ^D	10	Match IRFs
Investment adj. costs in T	ϕ^T	3	Match IRFs
Investment adj. costs in N	ϕ^N	3	Match IRFs
Taylor rule inflation coefficient	ω^π	1.5	Standard value

Figure 1.6: IRF to a 2 quarters ahead anticipated 25bp contractionary U.S. interest rate shock-DSGE/VAR



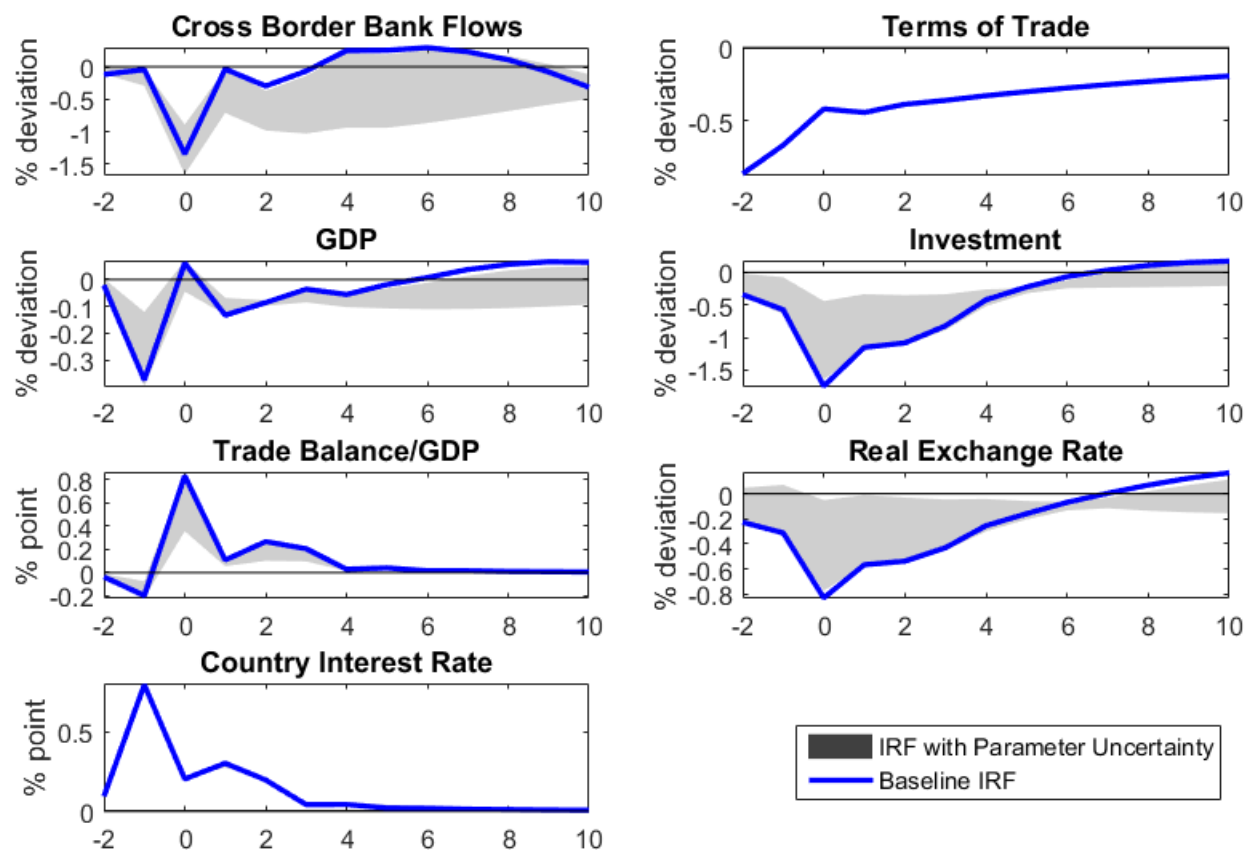
Note: Blue dashed lines denote the point estimates of impulse responses using simulated data from the theoretical model. Solid red lines denote the point estimates of impulse responses from the VAR system (1.5); 90% confidence bands are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, and Investment are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Real Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Confidence bands are computed through 1,000 bootstrap replications. Horizon is in quarters.

Figure 1.7: IRF to an Unanticipated 25bp contractionary U.S. interest rate shock-DSGE/VAR



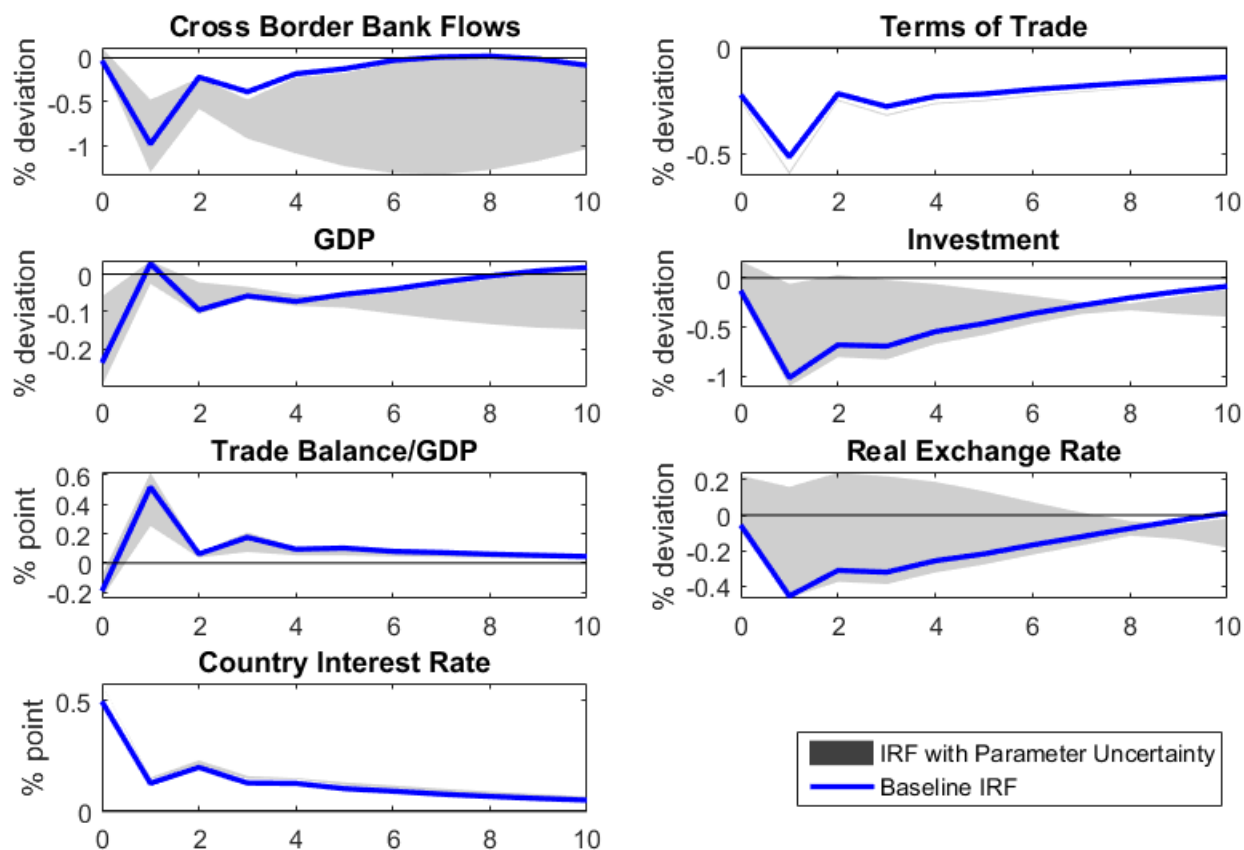
Note: Blue dashed lines denote the point estimates of impulse responses using simulated data from the theoretical model. Solid red lines denote the point estimates of impulse responses from the VAR system (1.5); 90% confidence bands are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, and Investment are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Real Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. Confidence bands are computed through 1,000 bootstrap replications. Horizon is in quarters.

Figure 1.8: IRF to an anticipated 25bp contractionary U.S. interest rate shock-Parameter Uncertainty



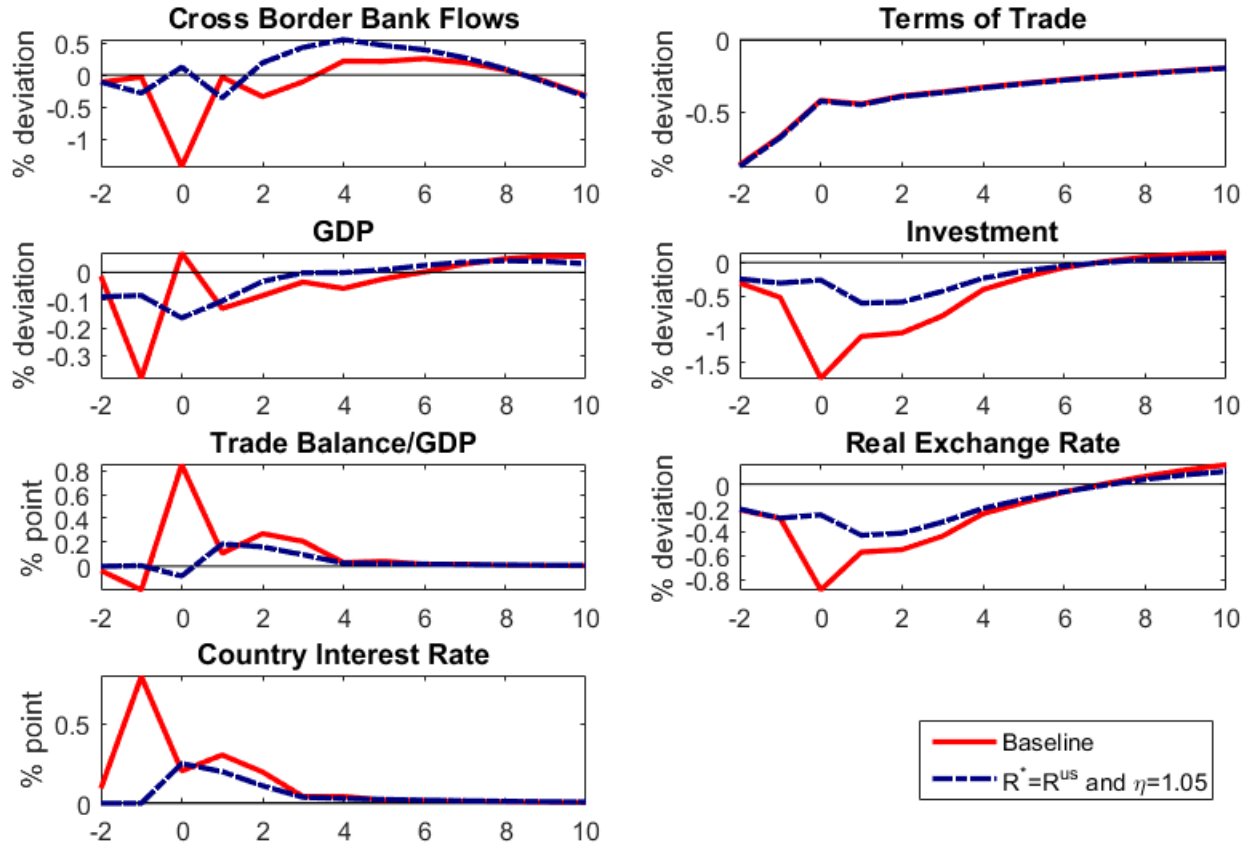
Note: Blue continuous line denotes the IRFs using the baseline calibration; grey shaded areas denote 90% probability bands for the responses of the variables when parameters are allowed to vary over the ranges reported in Table 1.7. Horizon is in quarters.

Figure 1.9: IRF to an unanticipated 25bp contractionary U.S. interest rate shock-Parameter Uncertainty



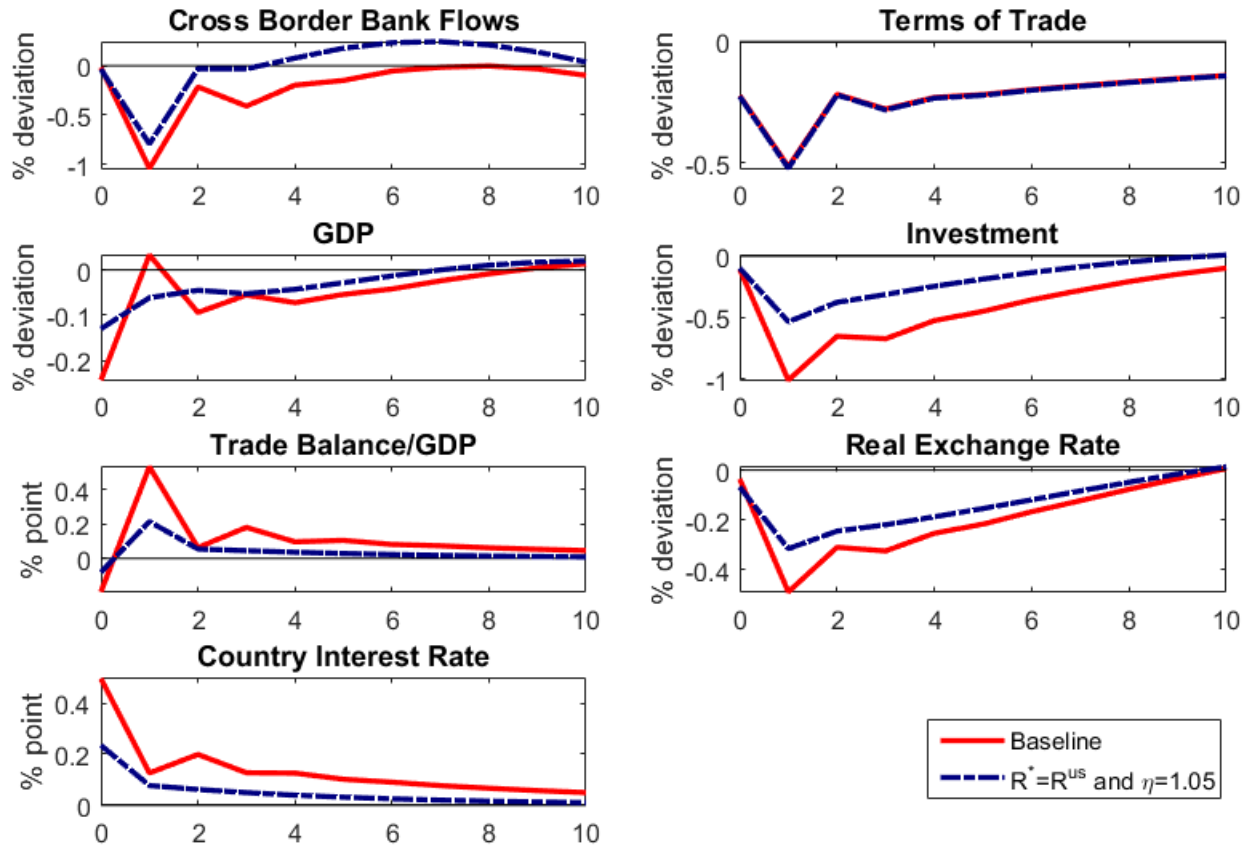
Note: Blue continuous line denotes the IRFs using the baseline calibration; grey shaded areas denote 90% probability bands for the responses of the variables when parameters are allowed to vary over the ranges reported in Table 1.7. Horizon is in quarters.

Figure 1.10: IRF to an anticipated 25bp contractionary U.S. interest rate shock-Transmission Channels



Note: Red continuous line denotes the IRFs using the baseline calibration; dashed blue line denotes the IRFs using the baseline calibration but eliminating the feedback from domestic macroeconomic conditions to the country interest rate and reducing the value of η^T to 1.05. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Horizon is in quarters.

Figure 1.11: IRF to an unanticipated 25bp contractionary U.S. interest rate shock-Transmission Channels



Note: Red continuous line denotes the IRFs using the baseline calibration; dashed blue line denotes the IRFs using the baseline calibration but eliminating the feedback from domestic macroeconomic conditions to the country interest rate and reducing the value of η^T to 1.05. Horizon is in quarters.

Chapter 2

Emerging Economies Business Cycles: The Role of Commodity Terms of Trade News

Joint with Nadav Ben Zeev and Evi Pappa

2.1 Introduction

Until recently it has been commonly accepted in the international macroeconomics literature that shocks to the terms of trade (henceforth, TOT) - price of exports relative to the price of imports - were an important determinant of macroeconomic dynamics in most emerging market economies (henceforth, EMEs; see, e.g., [Mendoza \(1995\)](#); [Kose \(2002\)](#)). In their latest article, however, [Schmitt-Grohe and Uribe \(2017\)](#) have challenged this traditional view by estimating annual country-specific SVARs for 38 poor and EMEs and showing that TOT shocks explain on average 10 percent of movements in aggregate activity. Other studies have analyzed the role of commodity prices, instead of the ratio of export to import unit value indices (see, e.g., [Fernández, González, and Rodríguez \(2015\)](#); [Shousha \(2016\)](#); [Fernández, Schmitt-Grohé, and Uribe \(2017\)](#)). All these works find that shocks to commodity prices explain around one third of business cycle fluctuations, but they have only considered the role of unanticipated shocks.

The starting point of our analysis is that many TOT movements are anticipated. For example, the increases in the TOT observed during the 2000s for many economies were largely due to rising commodity prices, driven by strong economic growth in countries such as China and India ([Kilian and Hicks \(2013\)](#)). To the extent that agents recognize the underlying causes of changes in the TOT, it is reasonable to assume that they are able to forecast these fluctuations. [Fernández, González, and Rodríguez \(2015\)](#) show that country spreads lead commodity prices in EMEs. This fact may suggest that agents change their assessment of economic conditions depending on the expected evolution of commodity prices. In this case, other high frequency variables should also reflect these expectations. [Chen, Rogoff, and Rossi \(2010\)](#) find that, for a sample of small commodity exporters, the exchange rates have robust power to predict the evolution of commodity prices. Moreover, futures commodity prices can be thought of as providing “forecasts” of commodity prices ([Chinn and Coibion \(2014\)](#)). Hence, it is important to examine whether anticipated movements in the TOT matter for business cycle dynamics of small emerging countries.

This paper studies the macroeconomic effects of news shocks to the TOT. There has recently been a renewed interest in theories of expectation-driven business cycles, focusing in particular on the effects of news shocks: shocks which are realized and observed before they materialize.¹ Our identification assumptions differ in one critical way from those in

¹[Beaudry and Portier \(2006\)](#) were the first to provide empirical evidence in favor of this hypothesis in the context of structural VARs. [Beaudry and Portier \(2006\)](#) and [Jaimovich and Rebelo \(2009\)](#) present theoretical models in which news about future productivity is a primary source of business cycle fluctuations. [Schmitt-Grohe and Uribe \(2012\)](#) estimate a closed economy DSGE model with flexible prices, which incorporates news about future fundamentals, and show that anticipated shocks account for around half of aggregate fluctuations in the U.S.

Beaudry and Portier (2006) and Barsky and Sims (2011) for the identification of TFP news. In our identification of TOT news shocks we do not impose the orthogonality restriction that news to the TOT cannot affect the TOT contemporaneously. Since TOT typically relate to the future value of storable goods, an anticipated future change in the TOT may cause a current movement in this variable through movements in inventories (see, e.g., Pindyck (2001); Roache and Erbil (2010)).²

Given the shortcomings of employing zero impact restrictions, we employ an alternative identification strategy for extracting news about TOT movements in the data. Our identification strategy relies on “medium-run” restrictions and builds on Uhlig (2003), Barsky and Sims (2011), and mainly on Kurmann and Sims (2017). In particular, our benchmark specification consists of country-specific quarterly VARs for Argentina, Brazil, Chile, Colombia, and Peru.³ Following Shousha (2016) and Schmitt-Grohe and Uribe (2017), our SVAR model consists of foreign exogenous and domestic endogenous variables. The exogenous variables are the commodity based TOT index (henceforth, CTOT), computed as the real price index of the country commodity export bundle, and the U.S. corporate bond (Baa) spread, which we use as an indicator for global financial conditions for emerging economies Akinci (2013). The domestic endogenous variables include: output, consumption, investment, the trade balance, the real exchange rate, and a measure of country-spreads, proxied by the JP Morgan EMBI Global Index. We identify CTOT shocks as the disturbances that best explain future movements in the CTOT at a horizon of five quarters and that can be correlated to current CTOT movements. In particular, following the evidence presented by Chen, Rogoff, and Rossi (2010) and Fernández, González, and Rodríguez (2015), we exploit variations in domestic macroeconomic variables, exchange rates, and country spreads together with the exogeneity of CTOT to identify news about CTOT. Lifting the orthogonality condition comes at a cost since we are able to identify only a combination of shocks that maximize the forecast error variance of CTOT and it includes both unexpected shocks, as well as the anticipated component in the CTOT movements. For this reason, we call our extracted shocks “news-augmented CTOT shocks”.

²Beaudry and Portier (2006) use variations in stock prices to identify news about TFP. Following their approach, we could use fluctuations in commodity future prices to extract news shocks about the TOT. However, that would be problematic for two reasons. First, we could not have used the zero restriction that changes in future are orthogonal to current movements in the TOT. Second, since time varying risk premia is a relevant determinant of commodity future prices (see, e.g. Kaminsky (1990); Baumeister and Kilian (2016)), extracting information for fundamental movements from those series would not have been straightforward.

³Commodities account for at least 30 percent of total exports for this set of Latin American countries. Fernández, González, and Rodríguez (2015) and Shousha (2016) use a similar set of countries in their analysis and our results can be easily comparable to theirs.

News-augmented CTOT shocks explain, on average, 49 percent of cyclical fluctuations, while traditional shocks to the CTOT recovered using the standard Cholesky decomposition (henceforth, Cholesky CTOT shocks), as in [Schmitt-Grohe and Uribe \(2017\)](#), explain on average half of those fluctuations.⁴ News-augmented CTOT shocks induce significant and persistent increases in output, consumption, and investment. The Trade Balance also increases significantly for several periods after the shock and spreads decrease significantly. This fact confirms the findings of [Fernández, González, and Rodríguez \(2015\)](#) and [Shousha \(2016\)](#), who suggest that unexpected commodity price shocks are important in Latin American countries because they reduce country spreads causing larger expansions that would otherwise occur. Finally, news-augmented CTOT shocks appreciate the real exchange rate with a lag.

We perform various robustness analysis and extensions to the benchmark model. First, our results hold even when we use different horizons to maximize the forecast error variance of CTOT. Second, we assess the response of the economy in three cases: when we incorporate government expenditure in our benchmark SVAR; when we replace the Baa spread with the federal funds rate or the real 3-month Tbill rate; and when we include stock prices and commodity futures in the SVAR. Third, we show that our results hold using standard TOT series, computed as the ratio between price of exports and price of imports at quarterly and annual frequency, as in [Schmitt-Grohe and Uribe \(2017\)](#). Results are robust to extending the sample of countries to other emerging economies and when we consider separately countries with fixed and flexible exchange rate regimes. Finally, our conclusions still hold if we include the international variables, CTOT and the Baa corporate spread, in an exogenous block.

In a second step, we disentangle news and unanticipated shocks from the extracted news-augmented CTOT series. To do so, we use a principal components analysis on the movements between future realized changes in CTOT and the recovered news-augmented CTOT shocks. In particular, we extract two orthogonal factors and impose that anticipated shocks should lead to positive changes in the CTOT in future periods, while unexpected shocks should result in responses of the CTOT that are non-increasing. The identified anticipated component of the CTOT shock explains between 46 percent in Argentina to 60 percent in Peru of the identified news-augmented CTOT shocks. After recovering the anticipated and unexpected component of the CTOT shocks we investigate how the responses of the macro variables differ with respect to the two shock components. While

⁴[Schmitt-Grohe and Uribe \(2017\)](#) find that TOT surprise shocks explain on average 10 percent of output fluctuations in EMEs. However, the Forecast Error Variance (FEV) increases up to 19 percent if we consider only Argentina, Brazil, Colombia, and Peru, which are the countries considered in our sample and to 27 percent if we consider all the Latin American countries of their sample.

anticipated CTOT shocks lead to persistent increases in investment, trade balance and output on impact, and have significant positive lag effects on consumption, surprise shocks to the TOT induce a transitory increase in consumption, output and investment, and reduce the trade balance. In line with previous findings of [Fernández, González, and Rodríguez \(2015\)](#), the significant and persistent response of the country spread to the anticipated TOT shock reflect that high frequency variables also incorporate information about news.

Finally, we also disentangle the news-augmented CTOT shocks to a supply and a demand component following [Blanchard and Quah \(1989\)](#). We estimate a SVAR with world GDP growth and the identified series of news-augmented TOT shocks and take advantage of the fact that supply shocks, such as oil discoveries, should affect world output in longer horizons, while demand shocks – i.e., “price shocks” – should not. The average responses to a supply-driven news-augmented CTOT shocks are consistent with the findings of [Arezki, Ramey, and Sheng \(2017\)](#). Our results indicate that supply news-augmented CTOT shocks are more important for agricultural and oil exporters (Argentina and Colombia), while demand news-augmented CTOT shocks are more important for exporters of metal commodities (Chile and Peru).

The remainder of the paper is organized as follows. Section 2.2 describes the econometric framework. Section 2.3 presents the benchmark empirical results and also reports results from additional robustness exercises and extensions. Section 2.4 describes the methodology used to disentangle news from unexpected shocks and demand from supply-driven shocks and their macroeconomic effects. Section 2.5 concludes.

2.2 Econometric Strategy

Our identification strategy relies on the Maximum Forecast Error Variance (MFEV) identification approach put forward by [Uhlig \(2003\)](#) and later extended by [Barsky and Sims \(2011\)](#) and [Kurmann and Sims \(2017\)](#). To identify the news-augmented TOT shocks, we need to estimate first a SVAR that includes the main transmission channels of TOT shocks. As explained in [Barsky and Sims \(2011\)](#), an appealing way to identify news shocks to a fundamental, which is driven by an unanticipated shock and a news shock, is to estimate a reduced-form multivariate VAR where all variables, including the fundamental itself, are regressed on their own lags, as well as the other variables’ lags. Then, the resulting VAR innovations are used to search for the structural shock that satisfies the medium run restrictions. Following [Kurmann and Sims \(2017\)](#), we (a) extract a news-augmented CTOT shock that accounts for the maximum FEV share of CTOT at one truncation horizon, $H=5$; (b) do

not impose that the news shock is orthogonal with respect to the innovation in CTOT.⁵ According to [Chinn and Coibion \(2014\)](#) and [Husain and Bowman \(2004\)](#), the optimal horizon for predicting commodity prices varies between one and two years. We choose 5 quarters for the anticipation horizon as an average of those values and also, as we show in Section 2.3.4, this is the anticipation horizon for which the linear combination of shocks maximizes the FEV of CTOT two years ahead.

Following [Shousha \(2016\)](#); [Fernández, Schmitt-Grohé, and Uribe \(2017\)](#) and [Schmitt-Grohé and Uribe \(2017\)](#), our baseline SVAR model consists of foreign (exogenous) and domestic variables. The foreign variables include a country-specific CTOT series and the U.S. corporate bond (Baa) spread. We define CTOT as the real price index of the country commodity export bundle, where the weights are computed as a simple average of the export share of each good for the period 1994-2013 ([Shousha \(2016\)](#)). The Baa corporate spread, which is defined as the difference between Moody's Baa corporate bond yield and the Federal Funds rate and constitutes a relevant indicator of global financial conditions for emerging economies ([Akinci \(2013\)](#)), helps to control for another channel that is important for the transmission of world shocks to open economies. The domestic variables consist of six domestic macroeconomic indicators: output, consumption, investment, the trade balance, the real exchange rate, and a measure of country-spreads. We include country spreads, proxied by the JP Morgan EMBI Global Index, in the benchmark model for several reasons. First, CTOT news shocks generate foresight about changes in future fundamentals and lead to an undeniable missing state variable problem and, hence, non-invertible VAR representations. As is shown in [Sims \(2012\)](#), conditioning on more forward looking variables ameliorates or eliminates invertibility problems altogether. As a result, including country spreads in the VAR is essential for addressing the missing information problem. Second, according to [Uribe and Yue \(2006\)](#), country spreads respond endogenously to business cycle conditions in EMEs and might be affected by external and anticipated shocks, such as the shocks in the TOT. Finally, following [Chen, Rogoff, and Rossi \(2010\)](#) and [Fernández, González, and Rodríguez \(2015\)](#), the country spread and the exchange rates may contain useful information to identify expected movements in the CTOT. Details of all the series used are described in Appendix B.1.

The news shocks literature typically assumes that technology is driven by two exogenous components, one related to news about expected future changes in fundamentals and the other capturing unanticipated, or current shocks (see, e.g., [Beaudry and Portier](#)

⁵[Barsky and Sims \(2011\)](#) extract news about the fundamental instead by maximizing the sum of the FEV shares from impact period onwards and employ an orthogonality condition for the extracted news series relative to current movements in the fundamental.

(2006)). The news shocks are then identified by exploiting the contemporaneous dynamics of macroeconomic and financial variables and by imposing that they affect technology only with a delay. Thus, the main identification assumption is that technology evolves according to an exogenous process, which is independent of the rest of the variables. In order to identify news about CTOT, we also assume that the CTOT are exogenous for the small open economy, so we can use domestic macroeconomic and financial variables to identify expected fluctuations in this variable. Following the evidence presented by [Chen, Rogoff, and Rossi \(2010\)](#) and [Fernández, González, and Rodríguez \(2015\)](#), we allow variations in domestic macroeconomic variables, such as exchange rates, and country spreads to feed-back on the identification of news about CTOT. We depart from the existing literature for identifying exogenous news shocks by not imposing the zero impact restriction. The latter restriction is not appealing for the identification of commodity prices shocks since their storability implies that news in commodity prices can be hedged through movements in inventories and, as a result, will very often result to movements in commodity prices contemporaneously.⁶ Thus, it is very likely that news about future CTOT movements induce changes in CTOT today.⁷

Specifically, let the VAR in the observables be given by:

$$y_t = F_1 y_{t-1} + F_2 y_{t-2} + \dots + F_p y_{t-p} + F_c + e_t \quad (2.1)$$

where y_t represents the vector of observables, where the first two variables are the CTOT series and the Baa corporate spread, F_i are 8×8 matrices, p denotes the number of lags, F_c is a 8×1 vector of constants, and e_t is the 8×1 vector of reduced-form innovations with variance-covariance matrix Σ . The reduced form moving average representation in the levels of the observables is:

$$y_t = B(L)e_t \quad (2.2)$$

where $B(L)$ is a 8×8 matrix polynomial in the lag operator, L , of moving average coefficients and e_t is a 8×1 vector of reduced-form innovations. Then, the h step ahead forecast error is:

$$y_{t+h} - \mathbb{E}_t y_{t+h} = \sum_{\tau=0}^h B_\tau e_{t+h-\tau}, \quad (2.3)$$

⁶For a discussion of the inventory channel see [Pindyck \(2001\)](#) and [Roache and Erbil \(2010\)](#).

⁷Moreover, [Kurmman and Sims \(2017\)](#) show that, even if CTOT react to news shocks only with a delay, the zero impact restriction may still be violated in the data if the measure of CTOT is confounded by measurement error.

where B_τ is the matrix of moving average coefficients at horizon τ . The contribution to the forecast error variance of variable i attributable to shock j at horizon h is then given by:

$$\Omega_{i,j} = \sum_{\tau=0}^h B_{i,\tau} \gamma \gamma' B'_{i,\tau}, \quad (2.4)$$

where γ is a 8×1 vector corresponding to the j th column of a possible orthogonalization, and $B_{i,\tau}$ represents the i th row of the matrix of moving average coefficients at horizon τ . We index the CTOT shock as 1 in the e_t vector. The augmented news TOT shocks identification requires finding the γ which accounts for the maximum FEV share at one horizon H (the truncation horizon), and is allowed to affect CTOT movements on impact. Formally, this identification strategy requires solving the following optimization problem

$$\begin{aligned} \gamma^* &= \max \Omega_{1,2}(H) \\ \text{subject to } &\gamma' \gamma = 1 \end{aligned} \quad (2.5)$$

The restriction imposes on γ to have unit length, ensuring that γ is a column vector belonging to an orthonormal matrix. This normalization implies that the identified shocks have unit variance, but we do not restrict it to have a zero in its first entry, meaning that we allow the news-augmented CTOT shock to impact CTOT immediately.

We follow the conventional Bayesian approach to estimation and inference by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters. Specifically, we take 1000 draws from the posterior distribution of reduced form VAR parameters $p(F, \Sigma \mid \text{data})$, where for each draw we solve optimization problem (2.5); we then use the resulting optimizing γ vector to compute impulse responses to the identified shock.⁸ This procedure generates 1000 sets of impulse responses which comprise the posterior distribution of impulse responses to our identified shock. Our benchmark choices for the number of lags and truncation horizon are $p=2$ and $H=5$, respectively.⁹

2.3 Empirical Evidence

2.3.1 Data

We estimate five country-specific VARs. Data are quarterly and samples are as follows: Argentina 1994:Q1-2013:Q3, Brazil 1995:Q1-2014:Q3, Chile 1999:Q2-2014:Q3, Colombia

⁸Note that F here represents the stacked $(8 \times (p + 1)) \times 8$ reduced form VAR coefficient matrix, i.e., $F = [F_1, \dots, F_p, F_c]'$.

⁹We have confirmed the robustness of our results to different VAR lag specifications and truncation horizons. These specifications are presented in table 2.3 and in the online appendix.

1997:Q1-2014:Q3, and Peru 1997:Q1-2014:Q3. Appendix B.1 contains a detailed description of the data. Following [Shousha \(2016\)](#), we focus on Latin American commodity exporters, defined as countries where exports of commodities account for more than 30 percent of total exports, but later draw comparisons with samples with more emerging countries, when relevant. However, we found that pooling all set of Latin American and Asian countries together in the benchmark regression, as [Schmitt-Grohe and Uribe \(2017\)](#) do, was not a good idea for several reasons: a) the two regions are different both in CTOT performance and in terms of output dynamics, and b) while in Latin America there is a lack of potential supply conditions to determine the CTOT by smaller economies, in Asia some economies have become in a few years very influential in international markets.

2.3.2 Impulse Responses and Forecast Error Variance Decomposition

Figure 2.1 shows the estimated cross country average impulse responses of all variables to a one standard deviation news-augmented CTOT shock from the benchmark VAR. The bands in the figures are one standard error bands, where the standard error is the one corresponding to the standard error of the average estimate obtained from using the variances of the individual countries impulse responses. All responses should be interpreted as the typical responses of a Latin American country to the combination of anticipated and unanticipated exogenous increase in the CTOT. We present the individual responses in the Online Appendix.

News-augmented CTOT shocks increase CTOT on impact and persistently and the CTOT response reaches its peak in the fourth quarter. The shock induces an immediate increase in output and a delayed positive response of consumption and investment. These responses are reflected in a contemporaneous improvement in the trade balance. In response to the news-augmented shock in the CTOT, the country spread falls significantly on impact and persistently. This response confirms the findings in [Fernández, González, and Rodríguez \(2015\)](#) and [Shousha \(2016\)](#), who suggest that commodity price shocks are important in Latin American countries because they reduce country spreads causing larger expansions that would otherwise occur. The real exchange rate sluggishly appreciates. Turning to the variance decomposition in Table 2.1, we observe that news-augmented CTOT shocks explain on average 49 percent of output fluctuations and 31 percent of country spreads fluctuations.

News-augmented CTOT shocks are an important source of business cycle fluctuations for all the countries in the sample. Table 2.1 displays their contribution in explaining the

FEV of the macroeconomic variables included in the VAR. Although the relevance is similar across countries, news-augmented CTOT shocks are particularly important for Colombia and slightly less for Argentina. These differences in FEV may be associated with the different goods exported by each country, the structure of the economy, and also to the share of commodity exports over total exports. This can also be seen by the differences in the correlation of the shocks. On average the correlation of news-augmented CTOT shocks equals 0.24. Shocks are more correlated between Argentina and Brazil (0.48), and Chile and Peru (0.38) that are both agricultural and metal exporters, respectively, while the correlation of news-augmented CTOT shocks between Peru and Brazil is smaller, since the latter economy mostly exports agricultural products.

2.3.3 Comparison with Standard Cholesky CTOT Shocks

In this section, we assess how the news-augmented CTOT shocks compare to the standard CTOT shocks discussed in the literature. Typically, CTOT shocks are identified using a Cholesky decomposition in SVAR systems similar to the one of our baseline specification. Figure 2.2 displays the impulse responses of our baseline VAR when we identify CTOT shocks using the Cholesky decomposition and Table 2.2 reports the FEVDs for individual countries.

Figure 2.2 is comparable with the findings of [Schmitt-Grohe and Uribe \(2017\)](#). Our responses are not qualitatively very different from theirs besides the fact that the sample, the terms of trade index, and frequency of the data are different. The CTOT shocks induce an appreciation of the real exchange rate and an improvement on impact of the trade balance. Contrary to their findings, the initial consumption, and investment, responses to the CTOT positive disturbance are not significant and they increase with a lag. Turning to the variance decompositions (see Table 2.2), we also confirm the [Schmitt-Grohe and Uribe \(2017\)](#) findings. CTOT shocks explain over a two-year horizon on average 13 percent-23 percent of fluctuations in output, consumption, investment, and the trade balance. For Argentina and Colombia unexpected CTOT shocks explain almost 9 percent and 37 percent, respectively, of output fluctuations, while for the other countries, those numbers are comparable. Moreover, Cholesky CTOT shocks explain 19 percent of spread fluctuations. Overall, these results are very similar both qualitatively and quantitatively to the findings of [Shousha \(2016\)](#), who uses a very similar sample and terms of trade index to ours.

There is a noticeable similarity between the responses of the Cholesky CTOT shocks and the news-augmented CTOT shocks we extract using our methodology. Indeed, the correlation between the two shocks is on average 72 percent. This high correlation could be due to the fact that our shocks contain a mixture of surprise and anticipated CTOT

shocks. When we disentangle anticipated from surprise shocks in Section 2.4.1, we investigate further the relation between Cholesky and news-augmented CTOT shocks.

2.3.4 Alternative SVAR Specifications

In this section, we consider alternative VAR specifications for our empirical exercise. The impulse responses of all the exercises performed in this section are included in the Online Appendix. Here, for ease of exposition, we only present the share of variance explained by the news-augmented CTOT shocks in every exercise on average in Table 2.3.

2.3.4.1 Truncation Horizon

Taking both the results of [Chinn and Coibion \(2014\)](#) and [Husain and Bowman \(2004\)](#) and the truncation horizon for which news-augmented CTOT shocks maximize the two year FEVD of CTOT into account, in the benchmark VAR we use 5 quarters for the truncation horizon to recover our augmented CTOT news shocks. Yet, the same authors suggest that the optimal horizon for predicting commodity prices varies between one and two years. The second and third rows of Table 2.3 report results when we vary the truncation horizon to 3 quarters and 8 quarters. Changing the truncation horizon does not change results regarding the importance of the identified shocks in explaining aggregate fluctuations in emerging countries. Moreover, the IRFs, which are included in the online appendix, do not change significantly.

2.3.4.2 Government Spending

Since sovereign spreads are negatively affected by news-augmented CTOT shocks, the government reaction to such shocks might be key for shaping business cycle fluctuations. [Ilzetzi and Vegh \(2008\)](#) show that fiscal policy is procyclical in developing countries. The problem of procyclicality seems to be more acute in commodity rich nations since commodity related revenues can be a large proportion of total government revenues (see, e.g., [Sinnott \(2009\)](#)). [Céspedes and Velasco \(2014\)](#) study the behavior of fiscal variables across the commodity cycle and show that there is a negative relation between the fiscal balance and the behavior of commodity prices.

In this exercise, we introduce government expenditure as an additional endogenous variable in our benchmark SVAR. The fourth row of Table 2.3 presents the share of variance explained by the identified CTOT shocks when we control for movements in government spending in our analysis. The share of macroeconomic fluctuations explained by news-augmented CTOT shocks remains unchanged. In line with [Ilzetzi and Vegh \(2008\)](#), we

learn from this exercise that government reacts positively and persistently to the identified shock and such shocks explain 18 percent of government spending variability.¹⁰

2.3.4.3 Alternative Measures of World Interest Rates

Anticipated shocks that affect future commodity prices may also induce movements in the world real interest rate, which is the relative price of goods at different periods. Thus, the interest rate may be crucial for the transmission of news-augmented CTOT shocks. In our baseline specification, following [Schmitt-Grohe and Uribe \(2017\)](#) and [Fernández, Schmitt-Grohé, and Uribe \(2017\)](#), we include the U.S. corporate bond spread, which is a key financial variable for emerging economies ([Akinci \(2013\)](#)). However, including this variable does not affect significantly our results (see the seventh row of Table 2.3). Following [Shousha \(2016\)](#) and [Fernández, Schmitt-Grohé, and Uribe \(2017\)](#), we also consider specifications where we include the real three-month U.S. Treasury bill rate and the Federal Funds rate instead of the U.S. corporate spread.¹¹ Results of these exercises appear in the fifth and sixth row of Table 2.3, respectively. Unsurprisingly, changing the measure for the world interest rate does not modify our baseline results. When we proxy the world interest rate with the FFR and the real Tbill rate, results seem almost identical to the baseline specification apart from slight differences in the predictive power of the shock in explaining exchange rate and spread fluctuations. Overall, the effects of news-augmented CTOT shocks imply that the role of shocks to the CTOT in cyclical fluctuations in Latin American countries is far from negligible (i.e. they explain around 50 percent of output variations), as opposed to 25 percent in the results of [Shousha \(2016\)](#).

2.3.4.4 Financial Variables

Previous works in the news literature use financial variables to identify anticipated fluctuations in macroeconomic variables. As we mentioned before, commodity futures may be subject to time varying risk premia and may bias the identification of the shocks (see, e.g., [Kaminsky \(1990\)](#); [Baumeister and Kilian \(2016\)](#)). However, we think it is important to assess the response of these variables to the identified shocks and to see if they affect our main conclusions. Thus, in this subsection, we extend our baseline specification to include country specific stock price indexes and CTOT future prices. The eighth and ninth rows of Table 2.3 display the FEV for both specifications. Including either variable does

¹⁰See the Online appendix for the impulse responses.

¹¹The real Till rate is computed at monthly frequency as the difference between the nominal three months Tbill rate and the annualized U.S. CPI inflation over the last year. Then, we aggregate it to quarterly frequency by computing the average.

not change the relevance of news-augmented CTOT shocks to explain business cycles dynamics. As expected, news-augmented CTOT shocks are a relevant driver of fluctuations in CTOT futures (70 percent) and also of stock prices (39 percent).

2.3.4.5 TOT Shocks

In their conclusions, [Schmitt-Grohe and Uribe \(2017\)](#) suggest that an improvement in their empirical model could stem from entertaining the hypothesis that commodity prices are a better measure of the TOT than aggregate indices of export and import unit values, especially for countries whose exports or imports are concentrated in a small number of commodities. In accordance with the existing literature (see, e.g., [Fernández, González, and Rodríguez \(2015\)](#); [Shousha \(2016\)](#)), we have estimated our baseline VAR using the commodity-based TOT index. In order to investigate whether our conclusions are sensitive to the measure of TOT used in the empirical model, we have re-estimated our benchmark model substituting commodity-based TOT with the TOT index. Results from this exercise appear in the tenth row of Table 2.3. Using the TOT series in our baseline regressions, as suggested by [Schmitt-Grohe and Uribe \(2017\)](#), reduces indeed the importance of news-augmented TOT shocks to explain cyclical fluctuations, but does not change the fact that these shocks explain a significant part of fluctuations in emerging countries. News-augmented TOT shocks explain on average 32 percent of output fluctuations.

2.3.4.6 The Schmitt-Grohé and Uribe (2017) Specification

In the previous sensitivity analysis we have compared our results with the ones of [Schmitt-Grohe and Uribe \(2017\)](#) by changing one assumption at the time. Here we continue by analyzing the empirical specification used in [Schmitt-Grohe and Uribe \(2017\)](#), in order to compare directly our empirical results with theirs and to show that differences are not due to the different sample, frequency, or variables included in the VAR. In this exercise, we use exactly the same sample and variables as [Schmitt-Grohe and Uribe \(2017\)](#). That is, we estimate country by country VARs using annual data for 38 emerging and poor countries that include the TOT, U.S. corporate spread, real output, private consumption, investment, the real exchange rate, and the ratio of trade balance to GDP.¹² In the eleventh row of Table 2.3 we present the share of variance explained by the identified TOT shocks in this exercise.

¹²The [Schmitt-Grohe and Uribe \(2017\)](#) data set is available online and includes the following countries: Algeria, Argentina, Bolivia, Botswana, Brazil, Burundi, Cameroon, Central African Republic, Colombia, Congo Dem. Rep., Costa Rica, Cote d'Ivoire, Dominican Republic, Egypt Arab Rep., El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Korea Rep., Madagascar, Malaysia, Mauritius, Mexico, Morocco, Pakistan, Paraguay, Peru, Philippines, Senegal, South Africa, Sudan, Thailand, Turkey, and Uruguay for the period 1980 to 2011.

News-augmented TOT shocks explain almost triple of the variance of output relative to the Cholesky TOT shocks in [Schmitt-Grohe and Uribe \(2017\)](#).¹³ When we repeat their exercise but using only the sample of Latin American countries that overlaps with our baseline sample, the contribution of news-augmented TOT shocks to explain output fluctuations increases to 28 percent.

2.3.4.7 The Exchange Rate Regime

Fluctuations of the nominal exchange rate have important effects on relative prices. Therefore, an interesting and important ingredient missing in the analysis so far is the exchange rate regime. [Broda \(2004\)](#) shows that countries with flexible exchange rate regimes have faster adjustment of relative prices and, thus, smoother real responses than the ones with fixed regimes, supporting the hypothesis of [Friedman \(1953\)](#). Since the selection of countries in our benchmark regressions is not sufficiently large to consider heterogeneity of exchange rate regimes across countries and across time, in this section we first extend our analysis to 10 emerging economies for which quarterly data are available.¹⁴ Then, we investigate whether differences in the exchange rate regimes alter our baseline results. In the first row of the sixth block of Table 2.3 we present average results from our baseline specification estimated with this extended sample. The importance of the terms of trade in explaining output fluctuations in the extended sample drops slightly as expected (see also results of [Schmitt-Grohe and Uribe \(2017\)](#)). Since averaging out between countries/times with flexible and fixed exchange rate regime can make results more blurry and might bias the real role of news-augmented TOT shocks, we next consider subsamples with fixed versus flexible exchange rate regimes. Following [Ilzetzki, Reinhart, and Rogoff \(2017\)](#), we consider as fixed exchange rate regimes the countries classified as “Pre-Announced Peg” and “Crawling Peg +/- 2%” in the Coarse Classification.¹⁵ Results for the two regimes appear in the next two rows of the sixth block of Table 2.3. Surprisingly, the flexibility of the exchange rate regime does not seem to affect substantially the predictive power of

¹³[Schmitt-Grohe and Uribe \(2017\)](#) show that TOT shocks explain 7 percent of GDP fluctuations in the specification that includes the Baa corporate spread.

¹⁴The countries in our extended sample include Argentina, Brazil, Bulgaria, Chile, Colombia, Ecuador, Mexico, Peru, South Africa, and Turkey. Appendix B.1 contains a detailed explanation of the countries included. Since for some countries in the extended sample we were unable to recover weights for constructing the CTOT index at quarterly frequency and since according to our results for the five LA economies considered using the CTOT or the TOT index in the VAR does not change significantly our results, we use the TOT index instead of the CTOT index in this exercise.

¹⁵The fixed exchange rate sample is composed by: Bulgaria 2001:Q1-2013:Q4, Ecuador 2000:Q1-2013:Q4, Peru 1997:Q1-2014:Q2. The flexible exchange rate sample is composed by: Argentina 2002:Q1-2013:Q4, Brazil 1999:Q1-2014:Q3, Chile 1999:Q2-2014:Q2, Colombia 1997:Q1-2014:Q2, Mexico 1994:Q1-2014:Q2, South Africa 1995:Q1-2014:Q2, Turkey 1996:Q3-2014:Q2.

the identified shocks in explaining output or real exchange rate fluctuations. Yet, news-augmented TOT shocks explain slightly more of the FEV of sovereign spreads for fixed exchange rates, which could be due to the fact that anticipated exogenous TOT shocks increase exchange rate risk for these economies. Overall, the IRFs, presented in the online appendix, do not differ significantly across the different exchange rate regimes.

2.3.4.8 Exogeneity of CTOT Shocks

For our identification procedure to be valid, CTOT must be exogenous. Clearly, CTOT is largely exogenous from a small open economy's perspective. In our benchmark VAR, following the literature on the identification of TFP news (see, e.g., [Barsky and Sims \(2011\)](#); [Kurmann and Sims \(2017\)](#)), the news shocks were identified as the linear combination of all other VAR innovations that maximize the residual forecast error variance of CTOT for a finite horizon. That is, we have used information from domestic variables to identify news-augmented CTOT shocks. We did so because by placing the CTOT in the external block we would be missing all the information about expected movements in the CTOT that is contained in the domestic block.

In this subsection we consider an alternative specification where CTOT and U.S. corporate spread are included in an exogenous block. Thus, we only use information from these two variables to identify the news-augmented CTOT shocks. In particular, we postulate that foreign variables are completely exogenous. Innovations in the world interest rate may affect contemporaneously the CTOT to take into account the phenomenon of financialization of commodity markets (see, e.g., [Cheng and Xiong \(2014\)](#)). Results for this specification are presented in the last row of Table 2.3. Even if in this case the information set to extract news-augmented CTOT shocks is smaller, the contribution of news-augmented CTOT shocks to explain business cycle fluctuations remains unchanged. Thus, our conclusions do not depend on this particular specification of the baseline SVAR.

2.4 Disentangling Shocks

In this section we identify news and surprise CTOT shocks using the news-augmented CTOT shocks described in the previous section and analyze the drivers of news-augmented CTOT shocks. In both cases, we assess the responses of domestic macroeconomic variables.

2.4.1 News versus Surprise CTOT Shocks

The shock we have recovered in the previous section is a combination of CTOT surprises and anticipated shocks. Ideally, one would like to disentangle the effects of anticipated from unexpected shocks. However, the nature of the CTOT series is such that recovering two structural shocks at a first stage is impossible. This is because anticipated future changes in the CTOT may cause current movements in this variable. For example, if a large reserve of oil is discovered somewhere, this discovery is likely to be associated with an expected future fall in the terms of trade for oil exporters. Since oil is storable, the future expected fall in the oil price will most likely induce a contemporaneous sell of oil in the spot market, causing the current price to fall. Thus, an anticipated future deterioration in the terms of trade causes a deterioration in the current terms of trade. As a result, we cannot use the standard zero restriction that other researchers have used for the identification of TFP news.

In this section we propose a way to disentangle the two shocks based on the shape responses of the CTOT to the unexpected and the news shocks. By definition, news about CTOT should induce increases in the CTOT in future periods that should be higher than increases in the CTOT on impact. Instead, CTOT surprise shocks should not induce hump-shaped responses. To formalize this argument and recover the two shocks, we resorted to the use of the principal components analysis.

We estimate the surprise and news components of our recovered shocks ex post using the method of principal components applied to the data matrix composed by the news-augmented CTOT series and the realized changes in CTOT over the next four quarters (i.e. $\Delta CTOT_t = CTOT_{t+4} - CTOT_t$).¹⁶ Considering that both series are exogenous for a small open economy, their joint dynamics can be described by two orthogonal unobservable factors: surprise and news shocks. Thus, we extract two factors from the matrix of the two series, which explain all the observed variation. We can represent the relation of the two series by:

$$\begin{bmatrix} \Delta CTOT_t \\ NACTOT_t \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \begin{bmatrix} Z_1 \\ Z_2 \end{bmatrix} = \Lambda Z_t \quad (2.6)$$

where $NACTOT_t$ denotes the news-augmented CTOT shocks, Z_1 and Z_2 are the two principal components, and the matrix Λ corresponds to the factor loadings. We interpret the two factors using the sign of the estimated factor loadings. In particular, if the

¹⁶As robustness, we have also considered the realized change of CTOT between 2 and 5 quarters ahead. Results do not differ from the ones using the realized change 4 quarters ahead and are available upon request.

ratio between the factor loadings of $\Delta CTOT_t$ and news-augmented CTOT shocks is positive (negative), then we classify the factor as a CTOT news (surprise) shocks. Surprise shocks should increase CTOT on impact but follow an non-increasing path afterwards, while news shocks should have a non-monotonic pattern. In other words, surprise CTOT shocks lead to largely transitory impulse responses of CTOT while news CTOT shocks should correlate positively with future movements in this series.

In Table 2.4 we present the percentage of the variation in the news-augmented CTOT series of our benchmark regression explained by the extracted principal component that captures anticipated movements in the CTOT. The news component explains between 60 percent in Peru to 46 percent in Argentina of the news-augmented CTOT shocks. Moreover, the identified series of CTOT news shocks are positively and strongly correlated across countries, ranging from 0.72 between Chile and Peru to 0.2 between Brazil and Chile. As expected, the correlation increases with the similarity of the export bundle.

After recovering the news and unexpected component of the CTOT shocks, we assess the responses of macroeconomic variables to both shocks using local projection methods (Jorda (2005)). This method has the advantage of being more robust to misspecification than VARs. In particular, considering that we have already identified the shocks, we estimate the following equation for each macroeconomic variable:

$$y_{t+h} = \alpha + \beta_h s_t + \sum_{j=1}^J \gamma_{j,h} y_{t-j} + \epsilon_t \quad (2.7)$$

where y_{t+h} denotes the value of the variable $\{y\}$ h periods after the shock, s_t denotes the recovered shocks (i.e. news and surprise CTOT shocks), and J represents the number of lags of y . For the baseline specification, we choose $J = 4$.¹⁷ Figures 2.3 and 2.4 display the average IRFs of macroeconomic variables to a one standard deviation CTOT news and surprise shock, respectively.

CTOT news shocks induce an increase in CTOT which reaches its maximum 5 quarters after the shock. GDP and trade balance increase on impact and persistently, reaching their maximum 6 and 3 quarters after the shock, respectively. Although the shock induces a contemporaneous and persistent decrease in the sovereign spread, investment and the real exchange rate react only with a delay. Consumption decreases initially but then increases persistently after four quarters.¹⁸

¹⁷Results are robust to using different values of J and also to adding lags of the shocks. Results are available upon request.

¹⁸The initial fall in consumption in response to a CTOT news shock is hard to rationalize using existing small open economy models. In the next section, we show that this response is associated with demand-driven news augmented CTOT shocks and analyze it more in detail.

By assumption, the response of the CTOT to surprise shocks is decreasing and also decreases the spread on impact. Yet, CTOT surprises induce a short live positive effect on GDP and investment. Compared to the CTOT news shock, the response of the trade balance is positive only on impact and then deteriorates with the decrease of CTOT. Finally, the real exchange rate does not react to these temporary fluctuations in the CTOT. If we compare to the Cholesky CTOT shocks (Figure 2.2), it appears that the IRFs to the Cholesky CTOT shock are somehow in between the IRFs to news and surprises. In fact, while the contemporaneous correlation between the surprise shocks and the Cholesky CTOT shocks is 0.36, the one between news shocks and Cholesky ones is 0.73. This indicates that indeed Cholesky shocks seem to contain both news and surprise components. Actually, if we decompose the Cholesky CTOT shocks between CTOT news and surprises, applying the principal component analysis we used for the news-augmented CTOT shocks, we find that the news component of the Cholesky shock explains between 48 percent in Chile to 37 percent in Argentina of the shock series. This fact indicates that the Cholesky CTOT shocks are not truly surprises. This result is important for the existing literature. Most of existing studies use the Cholesky decomposition to identify surprise shocks in the CTOT. Our analysis in this section reveals that the shocks recovered with the Cholesky identification contain also anticipated shocks, mainly due to the fact that news about the CTOT move the CTOT on impact. As a result, by using the Cholesky identification one identifies a combination of anticipated and surprise shocks. In order to recover the “true” unexpected CTOT shocks, the principal component analysis we propose is simple and overcomes possible difficulties in comparing theoretical and empirical predictions for the effects of CTOT shocks.

2.4.2 Supply versus Demand CTOT Shocks

The analysis of the previous section brings us naturally to this section where we attempt to disentangle demand from supply driven news-augmented CTOT shocks. To this end, we follow [Blanchard and Quah \(1989\)](#) and take advantage of the fact that supply shocks such as oil, or other commodity discoveries should increase productivity and output in longer horizons, while demand shocks – i.e., “price shocks” – should not. In particular, after having recovered the news-augmented CTOT shocks, we estimate a SVAR with our shock series and world GDP growth and impose the long run restriction on world output. We identify a supply (demand) shock as the one that affects (does not affect) GDP in the long run. The first column of Table 2.5 displays the contribution of supply shocks to explain news-augmented CTOT shocks and the second their contribution in explaining “pure” news shocks, identified in the previous section.

While supply shocks are more important for Argentina and Colombia, demand ones explain between 83 percent to 87 percent of the CTOT shocks in Chile and Peru. This might be due to the fact that the price of metals and copper is more associated with the state of the world economy than with supply conditions. On the other hand, discoveries or bad weather conditions in different regions of the world may affect more the evolution of CTOT in countries that export more agricultural products. After identifying the demand and supply shocks, we assess whether these shocks induce different responses of macroeconomic variables by estimating equation (2.7) with s_t now denoting the supply and demand shocks extracted from the SVAR with the long run restrictions described above.

Figures 2.5 and 2.6 display the average IRFs to a news-augmented CTOT shock driven by global supply and by global demand, respectively. The news-augmented CTOT shock that is associated with a permanent change in world GDP induces a persistent increase in the CTOT and also on GDP. Consumption and investment react positively but with a delay. These responses are comparable to the findings of [Arezki, Ramey, and Sheng \(2017\)](#). In particular, they can be rationalized with the two sector model they develop in their paper. Although the timing of the responses is different since they look at oil discoveries that take place 5 years in advance, qualitatively the responses are comparable. Thus, our results complement their findings since they focus on the effects of oil discoveries on the local economy, while we focus on world supply-driven news about international prices.

Demand-driven news-augmented CTOT shocks also induce a persistent increase in the CTOT. However, unlike supply shocks, they induce a fall in consumption on impact.¹⁹ This negative response in consumption helps to explain partially the more persistent increase in the trade balance. Finally, the real exchange rate does not react to this shock while the response of the sovereign spread is short lived.

2.5 Conclusions

The TOT of many commodity-exporters small open economies are subject to large shocks that can be an important source of macroeconomic fluctuations. The literature, which so far has been based on calibrated business-cycle models, has traditionally suggested this to be the case. In their recent article, [Schmitt-Grohe and Uribe \(2017\)](#) have challenged this

¹⁹The fall in consumption, also observed in response to pure CTOT news shocks in the previous section, is difficult to justify theoretically since the induced wealth effect of news about better future CTOT should increase consumption on impact. Moreover, the fall in the country spread should also ease borrowing constraints and increase consumption. Given that we have checked that government consumption does not crowd out private consumption after such news, the only possible explanation we can offer is that, after receiving news about increases in the price of metals, agents increase inventories and decrease metal sales. Given that financial frictions in these countries might affect borrowing, the reduction in sales and borrowing lead to a temporary fall in consumption after the news materialize.

view by providing evidence from SVAR that shows that unexpected changes in the TOT account for a small share of output variations in developing countries.

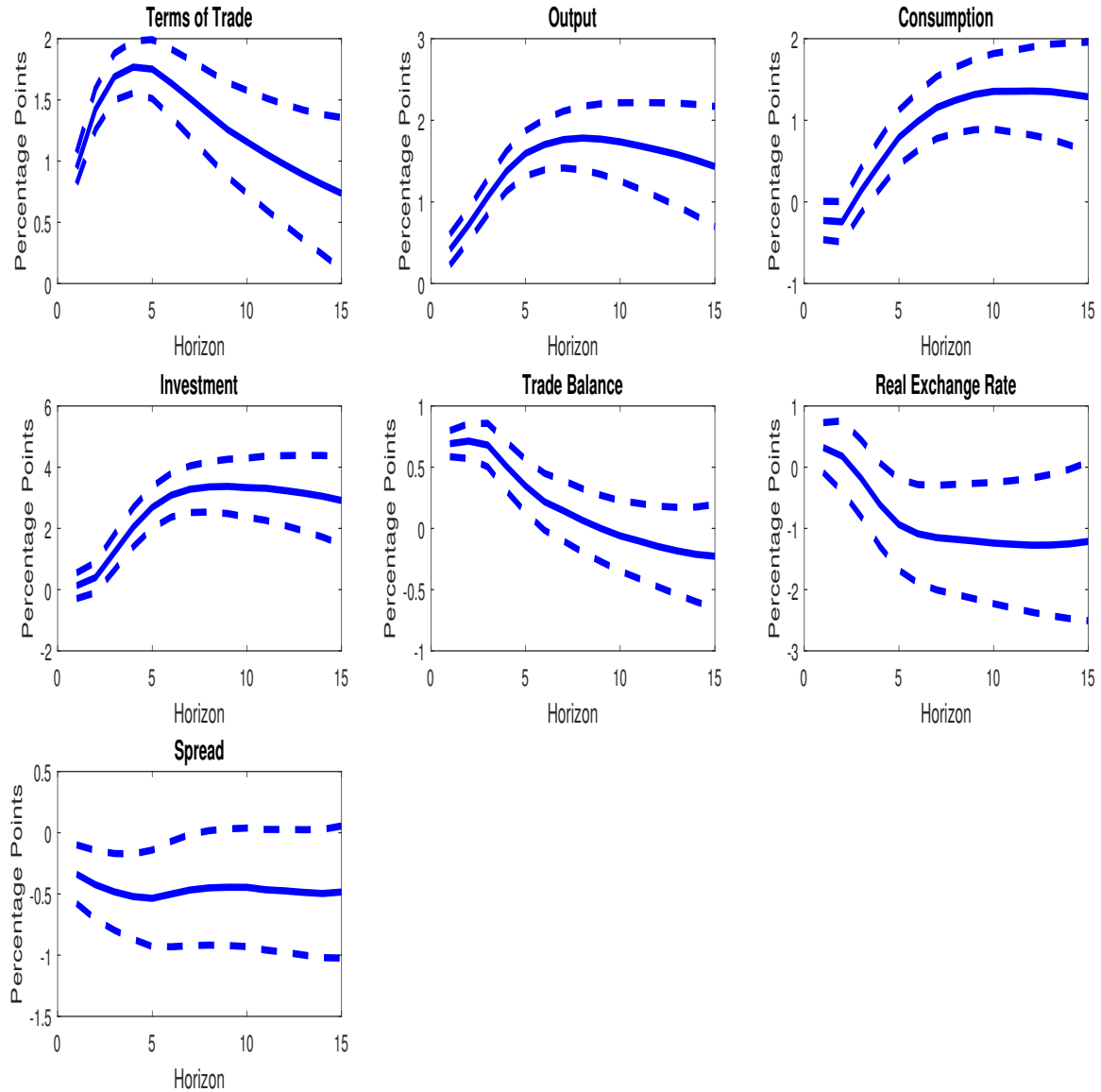
This paper extends the SVAR-based analysis of the role of shocks to terms of trade in [Schmitt-Grohe and Uribe \(2017\)](#) for five Latin American economies using the identification strategy in [Kurmman and Sims \(2017\)](#) that allows to identify news about the terms of trade. Unlike in existing studies (see, e.g., [Fernández, González, and Rodríguez \(2015\)](#); [Shousha \(2016\)](#); [Schmitt-Grohe and Uribe \(2017\)](#); [Fernández, Schmitt-Grohé, and Uribe \(2017\)](#)), where only unanticipated shocks are identified, we recover news-augmented CTOT shocks and show that they are an important source of cyclical fluctuations in emerging markets. We show that our results are robust to different assumptions and SVAR specifications.

Using a principal component analysis we disentangle anticipated and surprise CTOT shocks. News and surprises matter equally for movements in the CTOT. Due to the specific nature of CTOT movements, we show that the traditional Cholesky approach used in the literature for extracting CTOT surprise shocks also contains anticipated shocks. Our principal component analysis offers a way of identifying CTOT surprises, thus allows researchers to consistently study their effects on emerging market economies both in the data and in theoretical models. Finally, we develop a methodology for disentangling demand driven from supply driven news. We show that supply CTOT are more important for agricultural exporters, while demand CTOT shocks are more important for exporters of metal commodities.

All in all, our findings should be useful for modeling both surprise and news terms of trade shocks in small open economy real business cycle models and mapping model and data predictions. We conclude that the hypothesis about the role of the terms of trade as an important source of cyclical fluctuations in Latin America is, by no means, dead.

2.6 Figures and Tables

Figure 2.1: IRFs to a News-Augmented CTOT Shock



Notes: The solid lines are the average of the country-specific median responses to a one standard deviation news-augmented CTOT shock. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on 1000 draws taken from the posterior distribution of the VAR parameters, where the CTOT news shock is identified in accordance with the MFEV estimation procedure described in Section . Horizon is in quarters.

Table 2.1: Share of FEV Explained by News-Augmented CTOT Shocks: Country-Level SVAR Evidence

Country	CTOT	GDP	C	I	TB	REER	Spread
Argentina	73	35	30	29	10	18	8
Brazil	87	53	36	67	6	46	24
Chile	78	51	23	27	52	35	32
Colombia	83	64	40	52	27	18	42
Peru	83	44	26	29	65	38	48
Average	81	49	31	41	32	31	31

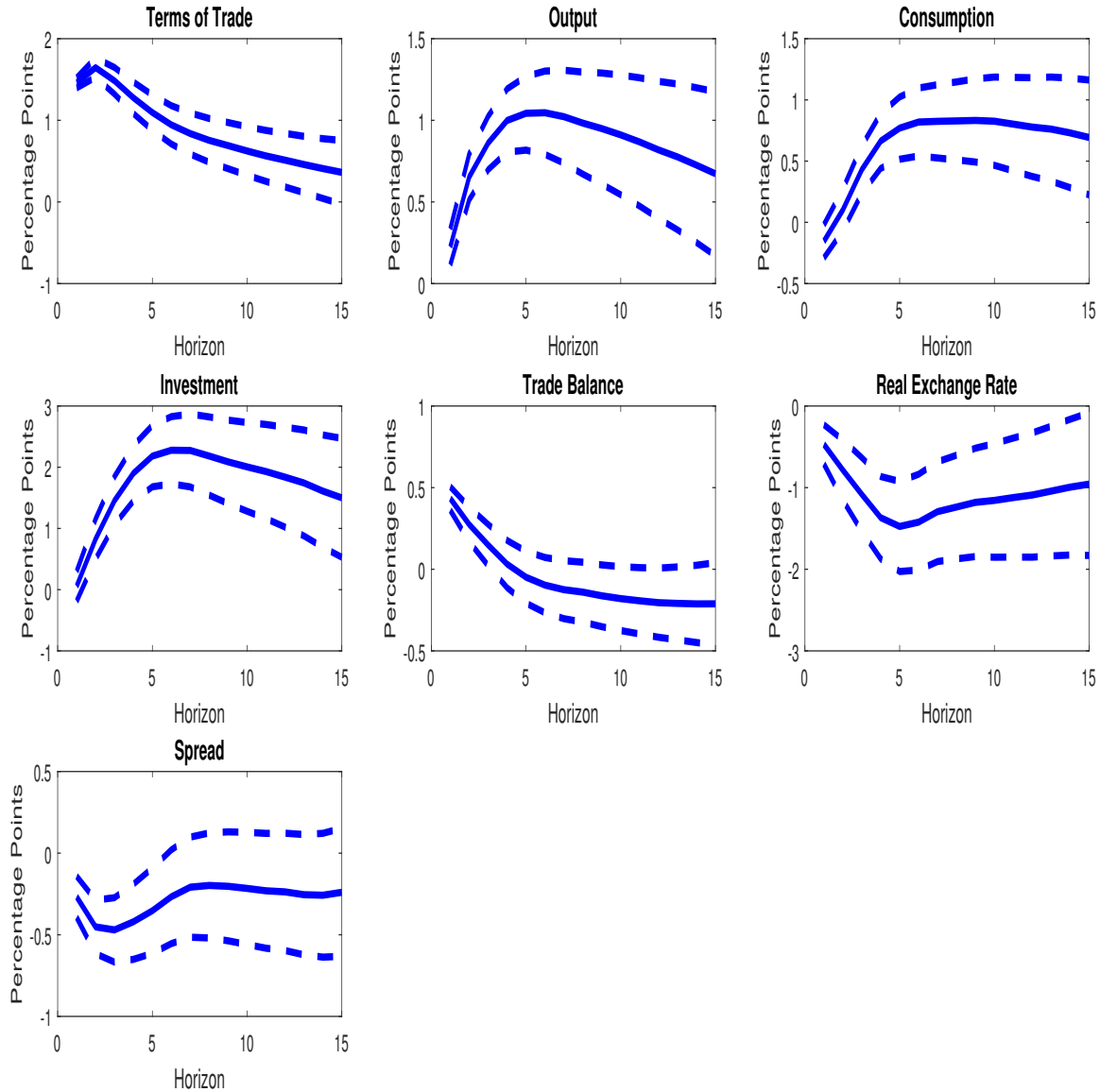
Notes: This table presents the estimated contribution of the news-augmented CTOT shock to the two-year variation in the variables obtained from each of the 5 country-level VARs. Average estimate is simple mean of the country specific estimates. Shares are expressed in percent. Column variables are: Terms of Trade (CTOT), Output (GDP), Consumption (C), Investment (I), Trade Balance to GDP ratio (TB), Real Exchange Rate (REER), and Sovereign Spread (Spread).

Table 2.2: Share of FEV Explained by Unanticipated CTOT Shocks: Country-Level SVAR Evidence

Country	CTOT	GDP	C	I	TB	REER	Spread
Argentina	60	9	12	6	8	4	4
Brazil	59	27	25	33	9	37	26
Chile	34	25	9	17	9	43	16
Colombia	66	37	23	40	13	13	25
Peru	44	16	14	16	24	8	26
Average	53	23	16	22	13	21	19

Notes: This table presents the estimated contribution of the Cholesky CTOT shock, identified using a Cholesky decomposition where the order of the variables is: [CTOT, BAA, Output, Consumption, Investment, Trade Balance, Real Exchange Rate, Spread], to the two-year variation in the variables obtained from each of the 5 country-level VARs. Average estimate is simple mean of the country specific estimates. Shares are expressed in percent. Column variables are: Terms of Trade (CTOT), Output (GDP), Consumption (C), Investment (I), Trade Balance to GDP ratio (TB), Real Exchange Rate (REER), and Sovereign Spread (Spread).

Figure 2.2: IRFs to a Cholesky CTOT Shock



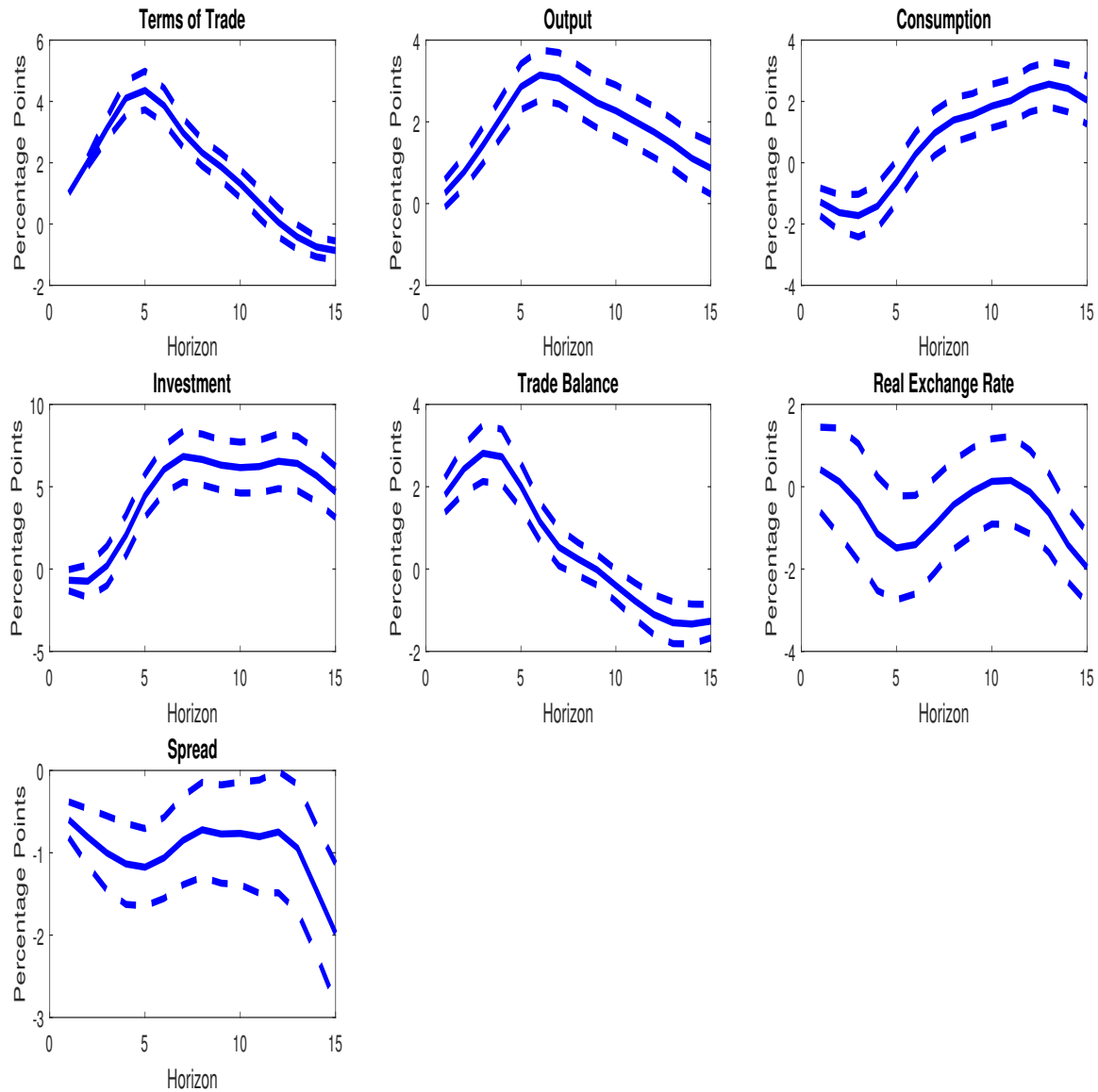
Notes: The solid lines are the average of the country-specific median responses to a one standard deviation Cholesky CTOT shock, identified using the Cholesky decomposition where the order of the variables is: [CTOT, BAA, Output, Consumption, Investment, Trade Balance, Real Exchange Rate, Spread]. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on 1000 draws taken from the posterior distribution of the VAR parameters, where the unanticipated CTOT shock is identified as the VAR innovation in CTOT using a Cholesky decomposition. Horizon is in quarters.

Table 2.3: Share of FEV Explained by News-Augmented CTOT Shocks for Alternative Specifications

Specification	CTOT	GDP	C	I	TB	REER	Spread	Fut	G	SP
Baseline (H=5)	81	49	31	41	32	31	22			
Baseline (H=3)	78	43	29	37	29	29	29			
Baseline (H=8)	70	48	27	33	34	30	27			
G	78	47	29	40	33	32	30		18	
FFR	80	48	32	42	31	30	30			
Real TBill	78	49	32	41	32	27	31			
CTOT	83	54	34	43	34	29	31			
Stock Prices	72	40	26	35	32	28	27			39
CTOT Futures	76	48	28	40	26	33	26	70		
Baseline with TOT Index	75	32	24	25	38	33	31			
SGU -Annual	75	21	16	16	17	17				
SGU (Our Sample) - Annual	75	28	12	10	8	12				
10 countries	62	28	22	21	26	26	25			
Fixed FX regime	52	31	26	24	29	20	32			
Flexible FX regime	61	28	19	21	26	27	22			
Baseline Exo. Block	99	48	30	42	28	33	36			

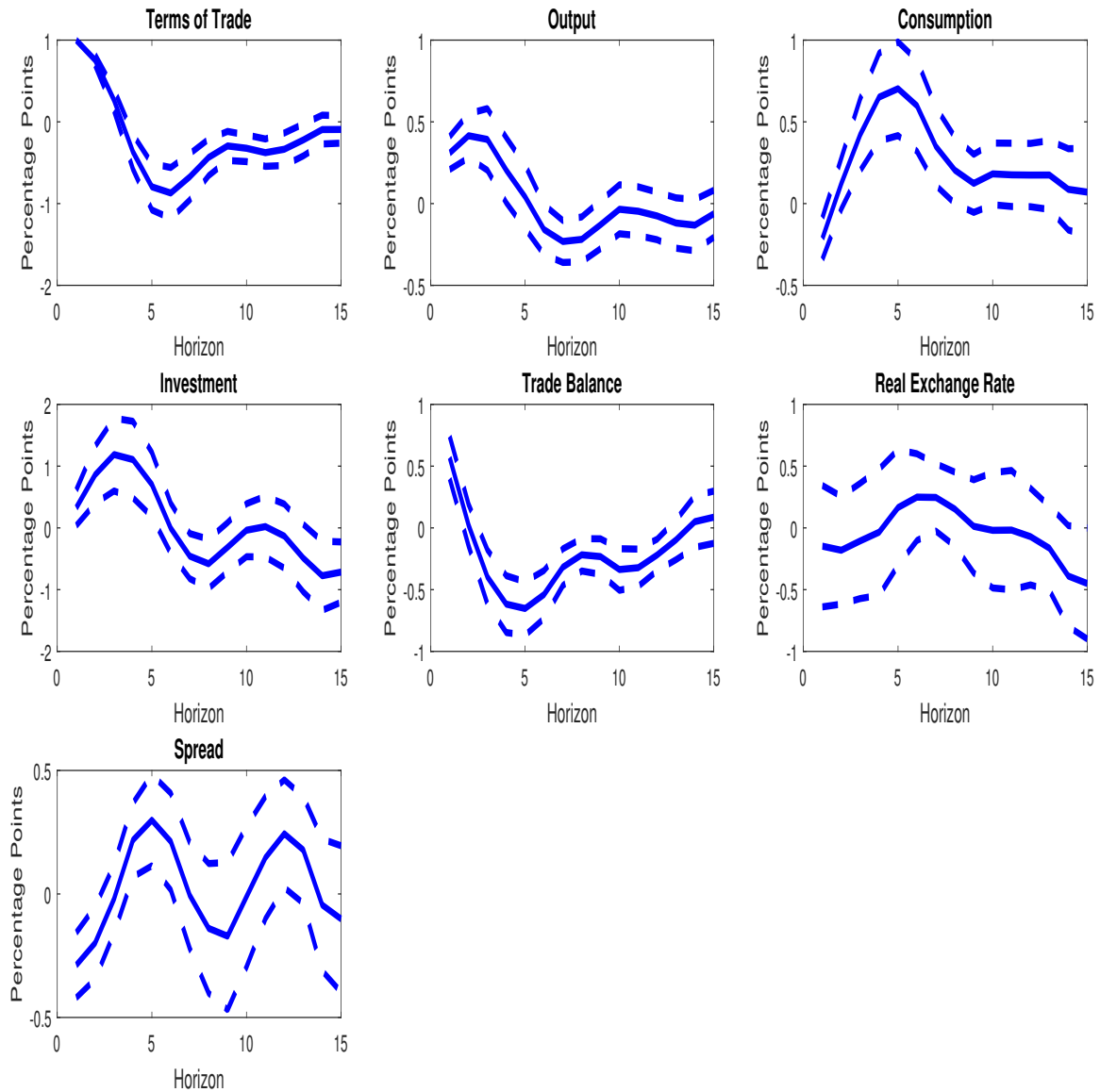
Notes: This table presents the average estimated contribution of the news-augmented CTOT shock to the two-year variation in the variables. Each row corresponds to an alternative SVAR specification described in Section 2.3.4. Shares are expressed in percent. Column variables are: Terms of Trade (CTOT), Output (GDP), Consumption (C), Investment (I), Trade Balance to GDP ratio (TB), Real Exchange Rate (REER), Sovereign Spreads (Spreads), Commodity Futures (Fut), Government Spending (G), and Stock Prices (SP). Rows specifications are: baseline specification with different truncation horizons, Government Spending (G, Section 2.3.4.2), Federal Funds Rate (FFR, Section 2.3.4.3), Real TBill Rate (Section 2.3.4.3), Stock Prices (Section 2.3.4.4), CTOT Futures (Section 2.3.4.4), Terms of Trade index (Section 2.3.4.5), SGU sample (SGU, Section 2.3.4.6), SGU Sample that overlaps with ours (SGU (LA Sample), Section 2.3.4.6), extended sample at quarterly frequency (Section 2.3.4.7), sample of countries with fixed and flexible exchange rate regimes (Section 2.3.4.7) and baseline specification where CTOT and BAA Spread are included in an exogenous block (Baseline Exo. Block, Section 2.3.4.8).

Figure 2.3: IRFs to a CTOT News Shock



Notes: The solid lines are the average of the country-specific median responses to a one standard deviation CTOT News shock, where the News shock is identified following the procedure described in Section 2.4.1. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on estimating equation 2.7 for all the variables. Horizon is in quarters.

Figure 2.4: IRFs to a CTOT Surprise Shock



Notes: The solid lines are the average of the country-specific median responses to a one standard deviation CTOT Surprise shock, where the Surprise shock is identified following the procedure described in Section 2.4.1. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on estimating equation 2.7 for all the variables. Horizon is in quarters.

Table 2.4: Contribution of the News Principal Component to Explain Total Variability

	CTOT News Shock
Argentina	46
Brazil	50
Chile	57
Colombia	52
Peru	58

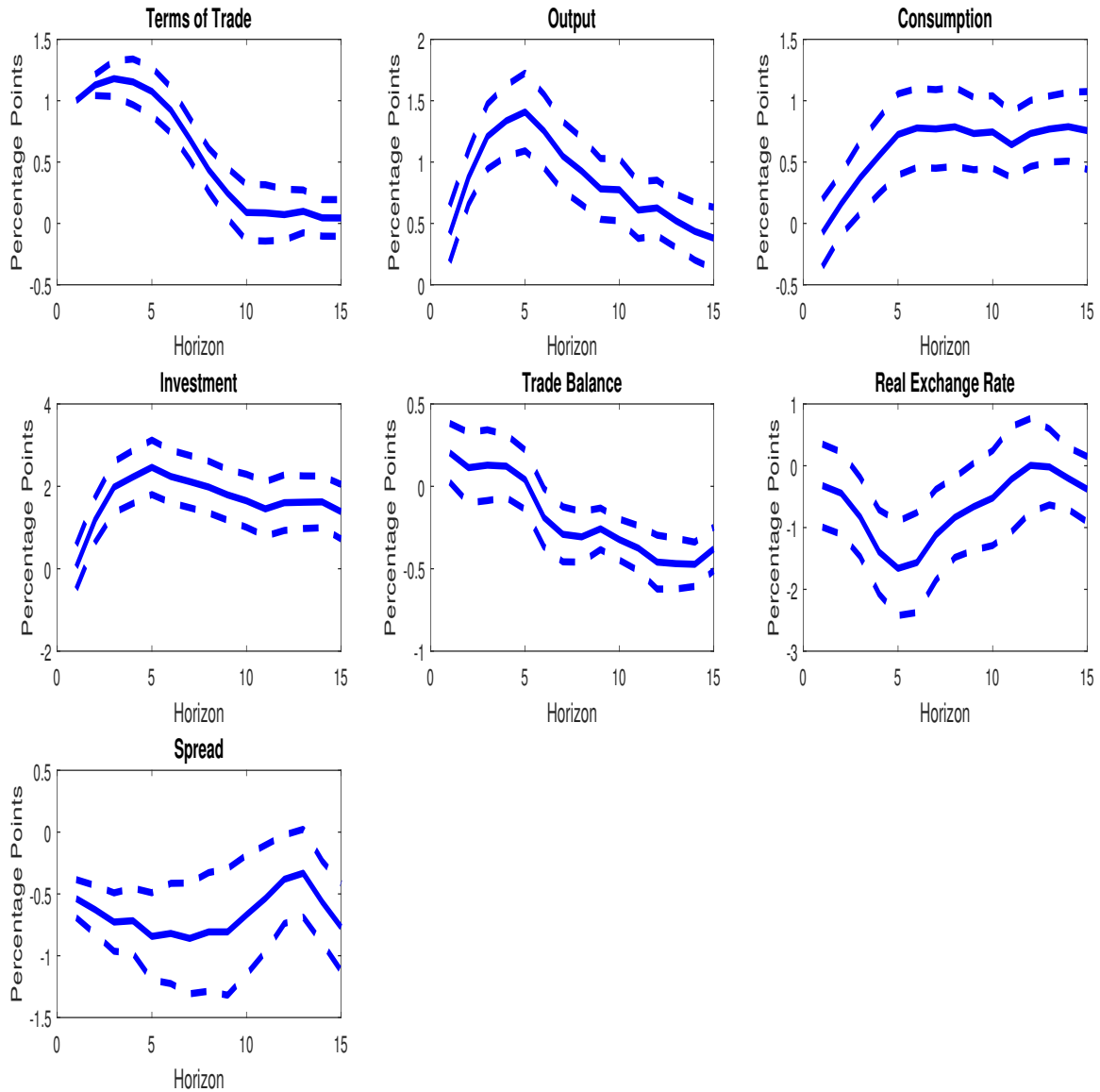
Notes: This table presents the percentage of the total variability of news-augmented CTOT shocks and the realized change in CTOT explained by the principal component interpreted as CTOT News Shock. The procedure to disentangle CTOT News and Surprise shocks is described in Section 2.4.1.

Table 2.5: Contribution of Global Supply Shocks to Explain CTOT News-Augmented and News Shocks

	News-Augmented	News
Argentina	27	57
Brazil	16	36
Chile	13	28
Colombia	34	61
Peru	17	34

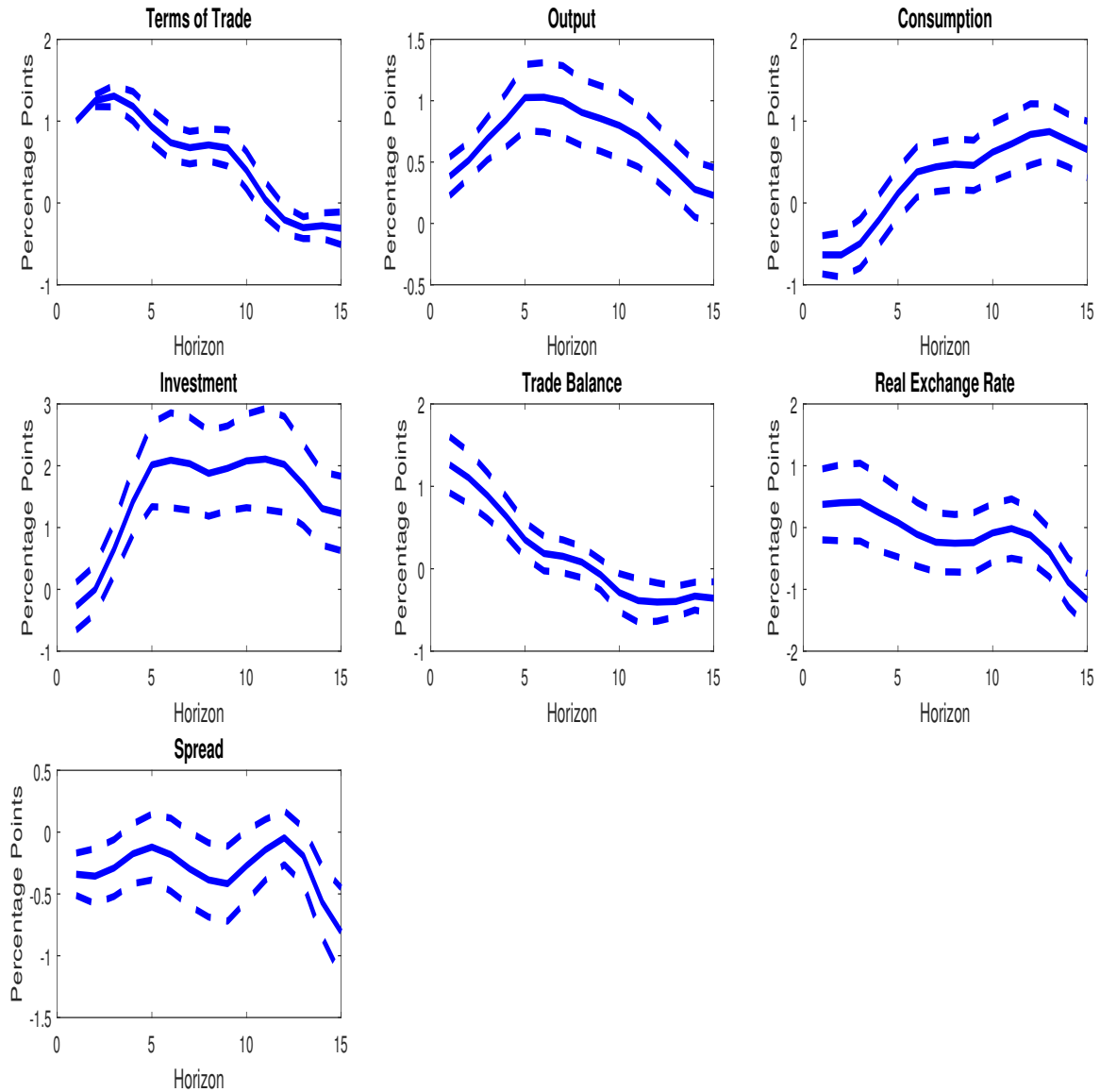
Notes: This table presents percentage of news-augmented CTOT shocks and CTOT News shocks explained by Supply shocks, which are identified following the procedure described in Section 2.4.2. News-augmented CTOT shocks are identified following the maximum FEV procedure described in Section 2.2. CTOT News shocks are identified following the procedure described in Section 2.4.1.

Figure 2.5: IRFs to a News-Augmented CTOT Supply Shock



Notes: The solid lines are the average of the country-specific median responses to a one standard deviation supply-driven news-augmented CTOT shock, where the shock is identified following the procedure described in Section 2.4.2. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on estimating equation 2.7 for each country. Horizon is in quarters.

Figure 2.6: IRFs to a News-Augmented CTOT Demand Shock



Notes: The solid lines are the average of the country-specific median responses to a one standard deviation demand-drive news-augmented CTOT shock, where the shock is identified following the procedure described in Section 2.4.2. The dashed lines are one standard error bands computed as the square root of the average variance across countries. The underlying country-specific estimates are based on estimating equation 2.7 for each country. Horizon is in quarters.

Chapter 3

Proxy-SVAR as a Bridge between Mixed Frequencies

Joint with Andrea Gazzani

3.1 Introduction

Macroeconomists increasingly incorporate information from financial markets, media, and the Web in their empirical analysis and models. The availability of this type of data, in particular from financial markets, allows researchers to draw information that was not available some years ago. Futures markets, for example, provide real-time information on expected policy decisions. Additionally, financial variables attract more attention due to the importance of recent financial-related events like the Great Recession or the European Sovereign debt crisis.

However, while macroeconomic aggregates are available only at the monthly or quarterly frequency, information from financial markets, media and Web is collected in real time or on a daily basis. When facing data sampled at different frequencies, the dominant approach still relies on temporal aggregation. The variables sampled at higher frequencies are converted to the lowest sampling frequency.¹ In this procedure, many properties of the original series are lost. Of particular interest for macroeconomists, temporal aggregation exacerbates the simultaneity problem that generates identification challenges in structural Vector Autoregressions (SVARs). More specifically, impulse response functions are not invariant to time aggregation as both the contemporaneous covariance of the residuals and the parameters of the Wold representation change. Therefore, analyses which rely on temporal aggregation can be strongly biased (see [Marcellino \(1999\)](#)).²

Mixed frequency techniques have consequently attracted a growing interest in recent years. Mixed Data Sampling (MIDAS) and Mixed-Frequency Vector Autoregressions (MFVARs) are two popular tools designed to deal with mixed frequency data (for a survey on the topic see [Forni, Ghysels, and Marcellino \(2013\)](#)). Both, however, exhibit some shortcomings due to feasibility and computational constraints. For example, the mismatch in frequencies cannot be too wide and/or the number of high/low frequency variables cannot be too large. An alternative approach, originally developed to overcome identification challenges in VARs, actually constitutes a remedy for temporal aggregation biases. This methodology, called high frequency identification in Proxy-SVAR (HFI-PSVAR), identifies

¹This aggregation usually follows either skip-sampling or averaging. Skip-sampling, or point-in-time sampling, is usually applied to stocks. In this case, the variables available at the higher frequency are converted to the lower frequency simply by taking the last value within the low frequency period (for example the last monthly observation within a quarter). In the averaging case, the variables are averaged over the lower frequency period and then observed only once for each of those low frequency periods (for example, the quarterly average of monthly data).

²Intuitively, the severity of the simultaneity problem that we face in time series analysis is decreasing with the sampling frequency. At the extreme, temporal aggregation can introduce simultaneity where there is none. Consider for example a monetary policy setup. By aggregating the daily interest rate to the monthly frequency, the interest rate series will incorporate the endogenous reaction of the central bank to the daily changes in (for example) inflation expectations, which occurred within the month.

exogenous variations in high frequency variables around particular events and uses them as proxies for the structural shocks of interest (e.g. [Gertler and Karadi \(2015\)](#)). Essentially, the researcher exploits the proxy together with the reduced form residuals of a VAR to identify a shock of interest.³ However, selecting key events for the phenomenon of interest is seldom straightforward and always arbitrary to a certain degree. Moreover, the Proxy-SVAR assumes that the proxy is orthogonal to the other structural shocks driving the system. Violations of this exclusion restriction would bias the analysis.

In this paper, we propose a new methodology, labeled “*Bridge Proxy-SVAR*”, that links data sampled at different frequencies, i.e. high frequency and low frequency variables, through the Proxy-SVAR.⁴ First, we identify the structural shock of interest in high frequency (HF) systems which are not subject to time aggregation and so characterized by less severe identification challenges (simultaneity). Second, we aggregate the series of shocks at the lower frequency, e.g. monthly or quarterly for macro variables. Third, we use the aggregated series of shocks as a proxy for the corresponding structural shock at this lower frequency (LF). Namely, we draw identifying restrictions for the LF representation from HF information.

Our methodology builds upon a crucial proposition: identification prior to temporal aggregation is superior to identification post temporal aggregation. We illustrate that this proposition holds analytically in a tractable case. In a bivariate setup where the frequency mismatch is two, we prove that, if the HF shocks are correctly identified, our methodology recovers the correct impact matrix. Monte Carlo experiments generalize the test of the methodology to a variety of cases and data generating processes (DGPs). In evaluating the performances, we focus on the Impulse Response Functions (IRFs) that summarize the relevant information from the estimation of VARs. Importantly, the Monte Carlo simulations also allow us to compare the *Bridge Proxy-SVAR* with the common naive practice of time aggregation (LF-VAR) and with the best possible estimation (HF-VAR). In the LF-VAR, HF variables are introduced as time aggregated so all the available information is compressed at LF. The HF-VAR, instead, is a counter-factual estimation where the LF variables are observable at HF. As such, the HF-VAR also provides the upper bound for the performances of the MF-VAR.

Our results show that the *Bridge Proxy-SVAR* (*Bridge*) is a suitable method for approximating the true underlying responses under different data generating processes. First, the

³This identification can be intuitively interpreted as an instrumental variable approach to VARs.

⁴In what follows, we consider a standard VAR for the high frequency estimation but the analysis can apply any econometric model more suitable for high frequency data. What matters is the identification of an unpredictable shock, orthogonal to other components.

Bridge greatly outperforms the LF-VAR in all cases and yields similar but less precise estimates to the HF-VAR. Second, our procedure can be applied in a simple manner, without computational burdens, even when the dimensionality of the system is large and when the frequency mismatch is wide. Third, we apply our methodology to assess the effects of monetary policy shocks in the US. Our benchmark is [Gertler and Karadi \(2015\)](#) as they apply the Proxy-SVAR. Their proxy consists of the series of monetary policy surprises built by [Gurkaynak, Sack, and Swanson \(2005\)](#). While this identification exploits key events for monetary policy, i.e. Federal Open Market Committee (FOMC) meeting days, we do not impose a priori any special role for these dates. Nonetheless, we find ex-post that the *Bridge* identifies shocks that are abnormally sizable on FOMC meeting days *vis-à-vis* non-FOMC days. Our series of shocks produces similar macroeconomic effects to those found in [Gertler and Karadi \(2015\)](#). Moreover, the monetary policy shocks we identify are immune to some criticisms posed in the literature on [Gertler and Karadi \(2015\)](#). This is related to the structural identification we employ and to the wide information set included in our HF-VAR. Finally, within our framework we can naturally take a further step consistent with the most recent works on monetary policy. In particular, [Gertler and Karadi \(2015\)](#) capture two distinct components on the path of interest rates, current and future, in their measure of monetary policy surprises, with opposite macroeconomic effect in the pre-crisis sample due to a strong informational content associated with shocks to the future rate.

The severity of temporal aggregation biases in VAR models is illustrated in [Marcellino \(1999\)](#) and [Forni and Marcellino \(2016\)](#). MF-VARs are the standard tools to handle data sampled at different frequencies. There are two main approaches to estimating VARs with mixed frequency data. The most popular one, developed by [Zadrozny \(1988\)](#), is based on a state space representation (a dynamic linear model). The system is driven by latent shocks whose economic interpretation is not straightforward. The presence of latent shocks implies that the Forecast Error Variance Decomposition (FEVD) of the system cannot be computed. Some examples of this approach include [Mariano and Murasawa \(2010\)](#), [Schorfheide and Song \(2013\)](#), and [Forni, Ghysels, and Marcellino \(2013\)](#). From a Bayesian perspective, [Eraker, Chiu, Foerster, Kim, and Seoane \(2015\)](#) and [Bluwstein and Canova \(2016\)](#) estimate the state space representation via Gibbs sampler.⁵ The second approach, proposed by [Ghysels \(2016\)](#), is more similar to standard VARs in being driven only by observable shocks. Contrary to model based on a state space representation, all the usual VAR tools are at the researcher's disposal. This particular VAR deals with series sampled at different frequencies through stacking: a HF variable is decomposed into several

⁵Some work as [Angelini, Banbura, and Runstler \(2010\)](#) have extended the mixed frequency state space representation to Factor models.

LF variables and directly employed in the VAR. For example, a monthly variable is introduced as three stacked series in a quarterly model. The shortcoming consists of the curse of dimensionality, i.e. parameters proliferation. Moreover, recovering the HF structural shocks from those in the stacked LF-VAR is not necessarily straightforward. Importantly for structural analyses, [Anderson, Deistler, Felsenstein, Funovits, and Koelbl \(2016\)](#) and [Anderson, Deistler, Felsenstein, Funovits, Koelbl, and Zamani \(2016\)](#) study conditions for identifiability of the HF representation of VARs from mixed frequency data.

Although MF-VARs are powerful tools that suit many analyses, they may not be applicable in some cases. For example, the MF-VAR may not be a feasible approach when the mismatch between high and low frequency variables is large (e.g. 30 in the case of monthly-daily data). Additionally, also the dimensionality of the system can be problematic. In fact, the stacked MF-VAR presents parameter proliferation problems when the researcher has to include many HF variables. Computational problems may arise in the state space MF-VAR when there are many unobservable states (LF variables).

The *Bridge Proxy-SVAR* is a useful alternative in these cases, since it provides relevant computational advantages over the MF-VAR in terms of frequency mismatch and dimensionality. On the other hand, the MF-VAR is a different econometric model that improves, over a LF-VAR, the VAR estimates of both the autoregressive matrix and the impact matrix of the shocks.⁶ The *Bridge Proxy-SVAR* only improves the impact matrix through information external to the LF-VAR, but still relies on the same autoregressive matrix of the LF-VAR. Additionally, the MF-VAR can assess the response of a HF variable on a LF variable, while the *Bridge* focuses exclusively on the reversal. Finally, the *Bridge Proxy-SVAR*, as the method developed by [Ghysels \(2016\)](#), relies purely on observables and not on latent variables and shocks as opposed to the state space MF-VAR.

The Proxy-SVAR methodology, developed by [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#), is a very recent development in the identification of SVAR. This method employs exogenous variations in one variable, which is included in the VAR system, as a proxy for the structural shock of interest. The proxy is assumed to be correlated with a structural shock of interest but orthogonal to other structural shocks. In practice, the proxy constitutes an instrument for the reduced form residuals of the VAR and is used for (partial) identification of the covariance matrix of the structural shocks. The clear advantage of this technique is that, as long as the proxy is a relevant and valid instrument, the identification relies on a much weaker set of assumptions than other identification schemes. For example, no assumptions are made on the contemporaneous relationship among the variables in the system. Moreover, [Carriero, Mumtaz, Theodoridis, and Theophilopoulou](#)

⁶Respectively, the A and B matrices in eq.(3.3).

(2015) have shown through Monte Carlo experiments that the PSVAR is robust to measurement errors. Lunsford (2015) provides a characterization of the asymptotic statistical properties of the Proxy-SVAR estimator.⁷ When the proxy is a strong (weak) instrument, the estimator for the impact of structural shocks is consistent (inconsistent and biased towards zero). Ludvigson, Ma, and Ng (2015) employ an iterative projection IV to jointly build multiple external instruments. Proxies are usually built from a narrative description of policy decisions⁸ or exploiting high frequency identification around some key events as in the already mentioned case of Gurkaynak, Sack, and Swanson (2005) and Gertler and Karadi (2015).

The *Bridge Proxy-SVAR* generalizes the HFI-PSVAR to those cases where there are no key events or when their selection is troublesome and arbitrary. The advantage of this methodology lies in the high frequency identification that may be cumbersome at low frequencies. At the same time, the high frequency shocks are used to instrument the reduced form residuals (prediction errors) of a LF-VAR. Intuitively, the *Bridge* always employs more information than a naive LF-VAR. Our approach remotely resembles the bridging equations which link data available at different frequencies through linear regression to produce nowcast and short-term forecast; e.g. Baffigi, Golinelli, and Parigi (2004) and Diron (2008). However, we exclusively focus on structural analysis and employ an instrumental variable approach.

After weighing pros and cons of our methodology versus the existing alternatives, we regard the *Bridge* as a particularly suitable tool for structural analysis on macro-financial linkages.

The remainder of this paper is organized as follows. Section 3.2 describes the *Bridge Proxy-SVAR* methodology. Section 3.3 presents the Monte Carlo experiments employed for testing. In Section 3.4, we apply the *Bridge* to study monetary policy in the US. Finally, Section 3.5 concludes.

3.2 Methodology

We introduce our methodology by summarizing the Proxy-SVAR identification (Section 3.2.1). In Section 3.2.2, we explain the steps that constitute the *Bridge Proxy-SVAR* methodology. First, we provide a general description of the identification. Second, an illustrative example shows how the *Bridge* can recover the correct impact matrix B in the

⁷In Jentsch and Lunsford (2016) the performances of different bootstrapping techniques are compared for the Proxy-SVAR. The suggest that the moving block bootstrap is the best option.

⁸See for example Stock and Watson (2012), Mertens and Ravn (2013) and Mertens and Ravn (2014).

VAR representation. On the other hand, when working with temporally aggregated data (LF-VAR) even the correct identification scheme cannot recover the true B matrix.

3.2.1 Proxy-SVAR

Consider the simplest possible VAR representation:

$$Y_t = AY_{t-1} + u_t \quad u_t \sim \mathcal{N}(0, \Sigma_u) \quad (3.1)$$

where Y_t and u_t are respectively n -dimensional vectors of endogenous variables and reduced form residuals with variance-covariance matrix Σ_u . The objective is to recover the structural form of the VAR, characterized by the vector of structural shocks $\varepsilon_t = B^{-1}u_t$:

$$Y_t = AY_{t-1} + B\varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \mathcal{I}) \quad (3.2)$$

Let us consider a bivariate VAR system, where X may represent a collection of variable and not necessarily a single variable:

$$\begin{bmatrix} X_t \\ y_t \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} X_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^X \\ \varepsilon_t^y \end{bmatrix} \quad (3.3)$$

The Proxy-SVAR is an identification strategy that partially identifies the unknown B matrix. Namely, $\begin{bmatrix} B_{12} \\ B_{22} \end{bmatrix}$ represent the impact response (IRFs) of the system to a structural innovation in the variable y . The Proxy-SVAR exploits the external information to the VAR system contained in z_t . z_t is assumed to be a proxy for, at least, a component of the true ε_t^y with the following (instrumental variable) properties:

$$\begin{aligned} \mathbb{E}[\varepsilon_t^y z_t] &= \mu \neq 0 \\ \mathbb{E}[\varepsilon_t^X z_t] &= 0 \end{aligned} \quad (3.4)$$

From the conditions in eq.(3.4), it directly follows that B_{11} is identified up to a scale-sign factor:

$$\mathbb{E}[u_t^y z_t] = \mathbb{E}[(B_{22}\varepsilon_t^y + B_{21}\varepsilon_t^X) z_t] = B_{22}\mu \quad (3.5)$$

In a similar fashion,

$$\mathbb{E}[u_t^X z_t] = \mathbb{E}[(B_{12}\varepsilon_t^y + B_{11}\varepsilon_t^X) z_t] = B_{12}\mu \quad (3.6)$$

The unknown parameter μ represents the share of the information in ε^y captured by z_t . B_{22} can be recovered only if μ is known, which in practice reflects the assumption $\mu = 1 \Rightarrow z_t = \varepsilon^y$. Otherwise, we cannot uniquely identify B_{22} and, as a consequence, B_{12} either. However, μ does not affect the ratio

$$\frac{B_{12}\mu}{B_{22}\mu} = \frac{B_{12}}{B_{22}} \quad (3.7)$$

meaning that B_{12} is identified up to B_{22} . We can interpret this procedure through an instrumental variable approach, in particular as two stages least squares (2SLS):

First Stage: regress u_t^y on z_t that yields $\hat{\beta}_I = B_{22}\mu$ and $\hat{u}_t^y = \widehat{B_{22}\mu z_t}$

Second Stage: regress u_t^X on \hat{u}_t^y where $\hat{\beta}_{II} = \frac{B_{12}}{B_{22}}$ by applying the definition of OLS.

The IRFs to ε^y are then computed across different horizons as:

$$\mathcal{IRF}_0^X = \frac{B_{12}}{B_{22}} \quad (3.8)$$

$$\mathcal{IRF}_n^X = A^{n-1} \mathcal{IRF}_{n-1}^X \quad \forall n > 0 \quad (3.9)$$

3.2.2 Bridge Proxy-SVAR

Traditionally, studies on monetary and fiscal policy have exploited narrative series or key events for identification. Such a strategy is hardly extendable to other areas of research. We therefore propose a more general and structural approach that employs HF information and, in this way, attenuates the time aggregation bias (see Section 3.2.3). Unlike the literature on mixed frequency, we do not model jointly the relationship between HF and LF variables, instead we exploit HF information to draw identification restrictions for the LF-VAR. As we show in Section 3.2.3.1, our approach exploits the superiority of identification prior to temporal aggregation over identification post temporal aggregation. First of all, we describe the steps in the *Bridge Proxy-SVAR* identification.

1. Define two VARs:

- (a) The first VAR, labeled High Frequency VAR (HF-VAR), incorporates the high frequency variables relevant for the analysis (e.g. financial daily). It includes the variable of interest y and all the other variables necessary for the identification of the shocks. We define this collection of other variables as the information set Ψ . Potentially, the researcher can use other (more appropriate, depending on the case) econometric models for HF data. Moreover, the applied identification

scheme should follow from economic theory.⁹ If these conditions are satisfied, then $\hat{\varepsilon}_t^y \approx \varepsilon_t^y$.

- (b) The second VAR, defined Low Frequency VAR (LF-VAR), includes variables at lower frequency. It features presumably macroeconomic aggregates and the variable y_t aggregated at lower frequency y_τ either by skip-sampling or averaging. The estimation of the LF-VAR yields the reduced form residuals $u_\tau = \begin{bmatrix} u_\tau^X & u_\tau^y \end{bmatrix}'$.

2. Aggregate the shocks estimated at HF to the LF:

$$\begin{aligned} z_\tau &= \frac{1}{m} \sum_{i=t}^{t+m} \hat{\varepsilon}_i^y && \text{averaging time aggregation} \\ z_\tau &= \hat{\varepsilon}_{mt}^y && \text{skip-sampling time aggregation} \end{aligned}$$

where m is the number of HF periods contained in a LF frequency period. If all sub-periods are the same then, in the averaging case, the correct aggregation scheme is actually given by $z_\tau = \hat{\varepsilon}_t^y$ (the shock in the first HF sub-period). If the assumptions in (1a) are satisfied, then, by construction, the proxy is exogenous $\mathbb{E}[\varepsilon_t^X z_t] = 0$ and relevant $\mathbb{E}[\varepsilon_t^y z_t] \neq 0$.

3. Use z_τ as a proxy for the structural shock of interest: instrument u_τ^y with z_τ and estimate the impact effect of a shock in y . This means that we are identifying the second column in the B matrix in eq.(3.2). We can see this procedure as 2SLS or directly as IV:

$$\begin{aligned} B_2 &= (z_\tau' u_\tau^y)^{-1} z_\tau' u_\tau \\ &= \begin{bmatrix} \mu B_{22} & \mu B_{12} \end{bmatrix} \\ &= \begin{bmatrix} 1 & B_{22}^{-1} B_{12} \end{bmatrix} \end{aligned} \tag{3.10}$$

so that the impact response to ε_τ^y is identified up to the impact effect on y itself. If we are confident that $\hat{\varepsilon}_t = \varepsilon_t$, then $\mu = 1$ and we can estimate the size of the shock from the standard deviation of the series obtained from the first stage regression.

Notice that the assumption in point 1, $\hat{\varepsilon}_t^y \approx \varepsilon_t^y$, is far more stringent than what we actually need. In fact, assume that the structural shock of interest can be decomposed as a sum of

⁹The higher the frequency at which they are imposed, the less identifying restrictions constrain the data and the more they are likely to hold.

two orthogonal *iid* components, weighted by the scalars μ_1, μ_2 :

$$\varepsilon_t^y = \mu_1 \varsigma_t + \mu_2 \phi_t \quad \varsigma_t \perp \phi_t \quad (3.11)$$

As explained in Section 3.2.1, the PSVAR partially identifies the B matrix and consequently we need to recover only a component of the HF shock ε_t^y , for example ς_t . Once again, this feature resembles a standard IV case where we exploit an exogenous variation in a variable of interest and not the whole exogenous variation. Recall indeed that eq. (3.4) does not assume the correlation being equal to 1, but only different from 0.

Next, we analyze how the Bridge Proxy-SVAR deals with data sampled at mixed frequencies. Starting from a general case, we move to a tractable example where, if a component of the structural shocks is correctly identified at HF, our proxy recovers the correct true impact matrix B .

3.2.3 Time Aggregation

As a first step, following [Forni and Marcellino \(2016\)](#), we illustrate the most general formulation. The objective of the analysis is to recover the IRF of the VAR system to a shock in the HF variable. The common practice consists of transforming the HF (indexed by t) at LF (indexed by τ) and running a VAR on time aggregated data. For the sake of simplicity, we consider a stationary case without deterministic components:

$$\begin{aligned} Y_t &= A(L)Y_t + B\varepsilon_t & \varepsilon_t &\sim \mathcal{N}(0, \mathcal{I}), t = 1, 2, \dots, T \\ [I - A(L)]Y_t &= B\varepsilon_t & \varepsilon_t &\sim \mathcal{N}(0, \mathcal{I}) \end{aligned} \quad (3.12)$$

Time aggregation is generally a two-step filter. First, the data is transformed through the filter $w(L)$ and, second, the series is made observable only every m periods through the filter $D(L)$. We consider the time aggregated representation under skip-sampling (or point-in-time sampling) since average sampling introduces a higher order MA component that further complicates the analysis. Nonetheless, we report in Appendix C.3 the same derivations for the averaging scheme and show that similar results hold in our Monte Carlo simulations. In the skip-sampling case, the filter $w(L) = 1$ does not produce any change. We apply the filter $D(L) = I + AL + \dots + A^m L^m$ so that the researcher can observe certain

variables only once every m periods:

$$\begin{aligned} D(L) [I - A(L)] Y_t &= D(L) B \varepsilon_t \\ Y_\tau &= C(L) Y_\tau + Q(L) \varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \mathcal{I}), \tau = mt, 2mt, \dots, T \\ Y_\tau &= C(L) Y_\tau + \xi_\tau \quad \xi_\tau \sim \mathcal{N}(0, \Omega) \end{aligned} \quad (3.13)$$

where $C(L) = D(L)A(L)$ and $Q(L) = D(L)B$. Ω is given by the squared contemporaneous elements in the $Q(L)$ matrix as the structural shocks are not auto-correlated. Time aggregation mixes different structural shocks at different times in ξ_τ .

3.2.3.1 An Illustrative Example

We focus now on a more specific case. We aim at assessing the effect of the shock in y , observable at HF, on x , available only at LF and time aggregated through skip-sampling. We consider a $VAR(1)$ representation and a mismatch between HF and LF equal to two, such that we can illustrate the methodology through simple algebra:

$$\begin{aligned} Y_t &= AY_{t-1} + B\varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \mathcal{I}) \\ (I - AL) Y_t &= B\varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \mathcal{I}) \end{aligned} \quad (3.14)$$

To move to the time aggregated representation (under skip-sampling), we apply the filter $D(L) = I + AL$:

$$\begin{aligned} D(L) (I - AL) Y_t &= D(L) B \varepsilon_t \\ (I - A^2 L^2) Y_t &= (I + AL) B \varepsilon_t \\ Y_\tau &= CY_{\tau-1} + \xi_\tau \quad \xi_\tau \sim \mathcal{N}(0, BB' + ABB'A') \\ Y_\tau &= CY_{\tau-1} + Q(L) \varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \mathcal{I}) \end{aligned} \quad (3.15)$$

where $C = A^2$ and $Q(L) = (B + ABL)$. Let us consider the system in extended notation in terms of the reduced form residuals u_t :

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^x \\ u_t^y \end{bmatrix} \quad (3.16)$$

In particular, assume that $B = \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix}$ so that we are in the standard Cholesky case, as in [Forni and Marcellino \(2016\)](#):

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix} \quad (3.17)$$

The temporally aggregated system is given by:

$$\begin{bmatrix} x_\tau \\ y_\tau \end{bmatrix} = \begin{bmatrix} a_{11}^2 + a_{12}a_{21} & a_{11}a_{12} + a_{12}a_{22} \\ a_{11}a_{21} + a_{21}a_{22} & a_{12}a_{21} + a_{22}^2 \end{bmatrix} \begin{bmatrix} x_{\tau-1} \\ y_{\tau-1} \end{bmatrix} + \begin{bmatrix} \xi_\tau^x \\ \xi_\tau^y \end{bmatrix} \quad (3.18)$$

where

$$\begin{bmatrix} \xi_\tau^x \\ \xi_\tau^y \end{bmatrix} = \begin{bmatrix} b_{11}\varepsilon_t^x + (a_{11}b_{11} + a_{12}b_{21})\varepsilon_{t-1}^x + a_{12}b_{22}\varepsilon_{t-1}^y \\ b_{21}\varepsilon_t^x + b_{22}\varepsilon_t^y + (a_{21}b_{11} + a_{22}b_{21})\varepsilon_{t-1}^x + a_{22}b_{22}\varepsilon_{t-1}^y \end{bmatrix} \quad (3.19)$$

In the temporal aggregation case, biases arise even if the identification exploits the correct Cholesky decomposition of the variance-covariance matrix of the reduced form residuals. The problem originates from the variance-covariance matrix observable at LF: $\Omega = BB' + ABB'A'$ which is different from the true BB' . Intuitively, in the LF-VAR the zero restriction constrains ε_t^y to have a zero effect over x for m periods instead of one (in this simple case $m = 2$). An analytical illustration of the time aggregation bias is reported in Appendix C.2.

Instead of imposing identification restrictions directly on the LF representation, we suggest identifying structural shocks from a HF system, which is not subject to temporal aggregation biases. The (temporally aggregated) structural shocks can be then employed to draw identifying assumptions in the LF-VAR representation. As the variable x is not directly observable at HF, the goodness of the identification is increasing in the amount of information included in the HF-VAR (Ψ). Moreover, Ψ should contain all the variables necessary to achieve a correct identification at this HF stage, which depends on the specific cases under examination.

In this stylized example, the HF system in the observables, assumed to be again $VAR(1)$, can be expressed in blocks as:

$$\begin{bmatrix} \Psi_t \\ y_t \end{bmatrix} = \Gamma \begin{bmatrix} \Psi_{t-1} \\ y_{t-1} \end{bmatrix} + \Phi \begin{bmatrix} \varepsilon_t^\Psi \\ \varepsilon_t^y \end{bmatrix} \quad (3.20)$$

The correct identification is fully achieved if x_t is spanned by the collection of variables that constitute the HF system and the LF-VAR (lagged):¹⁰

$$x_t \in \text{span} \{ \Psi_t, \Psi_{t-1}, y_{t-1}, x_{t-1} \} \quad (3.21)$$

Intuitively, the Proxy-SVAR uses information contained both in the HF system and the LF-VAR. It is the union of these two information sets that has to provide enough information on the unobservable x_t to achieve the correct identification. For simplicity, assume that Ψ_t perfectly incorporates the information contained in x_t . In applied research, if the HF system consists of financial variables, such an assumption is motivated by financial markets incorporating all available information. Moreover, a wide literature studies the reaction of financial markets to macroeconomic data releases. Imposing a recursive structure where y_t is ordered after Ψ_t yields the correct impact matrix B . In this way, identification restrictions do not rely on the temporally aggregated system but are drawn at HF.

Notice that, actually, we do not need to fully capture ε_t^y but only a component of it. In what follows, we assume that the proxy is given by a component of the true structural shock as defined in eq. (3.11). In order to be consistent with the skip-sampling temporal aggregation, we take the last HF shock within the LF interval:

$$z_\tau = \varsigma_t$$

We can express the last stage in the *Bridge* either as a two stage least square (2SLS) estimation or directly as IV. In the 2SLS case, we use z_τ it in the first stage regression

$$\xi_\tau^y = \beta_{1s} z_\tau + \eta_\tau \quad \eta_\tau \sim WN$$

where η is the error term, assumed to follow the distribution $iid \mathcal{N}(0, \sigma^2)$.¹¹

The estimated coefficient from the first stage is:

$$\begin{aligned} \hat{\beta}_{1s} &= \mathbb{E} [z_\tau' z_\tau]^{-1} \mathbb{E} [z_\tau' \xi_\tau^y] \\ &= \frac{\mathbb{E} [\varsigma_t (b_{21} \varepsilon_t^x + b_{22} \varepsilon_t^y + (a_{21} b_{11} + a_{22} b_{21}) \varepsilon_{t-1}^x + a_{22} b_{22} \varepsilon_{t-1}^y)]}{\mathbb{E} [\varsigma_t \varsigma_t]} \\ &= \mu_1 b_{22} \end{aligned} \quad (3.22)$$

¹⁰Notice that those are the necessary requirements to achieve the correct identification. In order to improve over the temporal aggregation practice, i.e. imposing restrictions directly on the LF-VAR representation, the conditions are much milder.

¹¹Henceforth, white noise (WN) will point at the error term in simple OLS equations, assumed to be distributed as $iid \mathcal{N}(0, \sigma^2)$ and uncorrelated with the independent variables.

If we employ the whole shock ε_t^y , then $\hat{\beta}_{1s} = b_{22}$ which is the true parameter in the HF representation. Notice that both requirements for a proxy are satisfied:

$$\begin{aligned} \mathbb{E}[\xi_\tau^y z_\tau] &= \hat{\beta}_{1s} = \mu_1 b_{22} \neq 0 & \text{IV relevance} \\ \mathbb{E}[\varepsilon_t^x z_\tau] &= 0 & \text{IV validity (by construction)} \end{aligned} \quad (3.23)$$

The fitted value from the first stage are given by:

$$\hat{\beta}_{1s} z_\tau = \mu_1 b_{22} \varsigma_t \quad (3.24)$$

The second stage regression is:

$$\xi_\tau^x = \beta_{2s} \left(\hat{\beta}_{1s} z_\tau \right) + \varphi_\tau \quad \varphi_\tau \sim WN \quad (3.25)$$

$$\begin{aligned} \hat{\beta}_{2s} &= \mathbb{E} \left[\left(\hat{\beta}_{1s} z_\tau \right) \hat{\beta}_{1s} z_\tau \right]^{-1} \mathbb{E} \left[\hat{\beta}_{1s} z_\tau \xi_\tau^x \right] \\ &= \mathbb{E} \left[\mu_1 b_{22} \varsigma_t^2 \right]^{-1} \mathbb{E} \left[\varsigma_t \xi_\tau^x \right] \\ &= (\mu_1 b_{22})^{-1} \mathbb{E} \left[\varsigma_t \left(b_{11} \varepsilon_t^x + (a_{11} b_{11} + a_{12} b_{21}) \varepsilon_{t-1}^x + a_{12} b_{22} \varepsilon_{t-1}^y \right) \right] \\ &= 0 \end{aligned} \quad (3.26)$$

meaning that the *Bridge* correctly recovers the Cholesky structure of the innovations. We obtain an equivalent result if we apply straight the definition of *IV* estimator:

$$\begin{aligned} \hat{\beta}_{Proxy} &= \mathbb{E} [z_\tau \xi_\tau^y]^{-1} \mathbb{E} [z_\tau \xi_\tau^x] \\ &= \frac{\mathbb{E} \left[\varsigma_t \left(b_{11} \varepsilon_t^x + (a_{11} b_{11} + a_{12} b_{21}) \varepsilon_{t-1}^x + a_{12} b_{22} \varepsilon_{t-1}^y \right) \right]}{\mathbb{E} \left[\varsigma_t \left(b_{21} \varepsilon_t^x + b_{22} \varepsilon_t^y + (a_{21} b_{11} + a_{22} b_{21}) \varepsilon_{t-1}^x + a_{22} b_{22} \varepsilon_{t-1}^y \right) \right]} \\ &= 0 \end{aligned} \quad (3.27)$$

Through this tractable case, we have shown analytically that the *Bridge* recovers the true impact matrix, whereas the correct Cholesky ordering imposed at LF introduces biases. The magnitude of these differences in a more general setup can only quantified through Monte Carlo experiments, presented in Section 3.3. Furthermore, we also test the robustness of the methodology to misspecifications and to limited information in the HF system and LF system employed by the *Bridge* (omitted variables).

3.3 Monte Carlo Experiments

Our design is similar to [Foroni and Marcellino \(2016\)](#) who compare the finite sample performances of the HF-VAR, LF-VAR (time aggregated), and the MF-VAR. In the latter, one variable is unobservable at high frequency but the econometrician only observes one out of three observations. We run the same experiment but we substitute the MF-VAR with the *Bridge*. Notice that the HF-VAR constitutes a “counter-factual” first best and an upper bound for the performances of the MF-VAR. Temporal aggregation follows skip-sampling, while in Appendix C.3 we report the main results under the averaging temporal aggregation scheme. We focus on the IRFs that summarize the relevant information on the estimation of the system. To be able to compare the IRFs under HF and LF representation, the IRFs at HF have to be treated in a consistent manner with the temporal aggregation scheme applied to the data.

The benchmark outline of the experiment is the following: we consider a VAR(1) DGPs and, for thirteen representative parametrizations, generate 1000 replications of 3000 HF observations. In a first step, the frequency mismatch is three, so that at LF we dispose of 1000 observations. For the sake of synthesis, we evaluate the performances of the three identifications through the lens of the *Mean Absolute Distance* (MAD) which measures the distance between the estimated and the true IRFs (cumulated over 8 horizons). For each replication, we compute the MAD and then we average over the whole set of replications.

The analysis begins with a stylized case that highlights the time aggregation bias alone. Then, one step at the time, we include further elements resembling the identification challenges that economists face in applied research.

3.3.1 Pure Time Aggregation

The LF-VAR and the *Bridge* temporally aggregate information in antithetical ways. In a LF-VAR, the aggregation occurs before identification while the *Bridge* identifies structural shocks at HF and then compresses them at LF. We are implicitly comparing the performances under these two temporal aggregation schemes.

The DGP follows the structure:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} \rho & \delta_l \\ \delta_h & \rho \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} e_t^y \\ e_t^x \end{pmatrix} \quad (3.28)$$

where $\begin{pmatrix} e_t^x \\ e_t^y \end{pmatrix} \sim \mathcal{N}(0, I_2)$. Basically, the innovations follow a recursive ordering structure that we correctly apply with the HF, LF and *Bridge*. We test 13 combinations of $\{\rho, \delta_l, \delta_h\}$ that represent different possible structures of the DGP.¹²

Figure 3.1-3.2 display an example of IRFs recovered with the three identifications. The HF-VAR and the *Bridge* perfectly recover the true IRFs, while the LF-VAR overestimates the size of the shock. Not surprisingly, Figure 3.3 points out that the HF identification is the best possible identification. An infinitesimal bias comes from the finite sample estimation of the HF-VAR system. The *Bridge*, which is by construction a second best option, performs very closely to the HF-VAR. Even if the *Bridge* and HF-VAR apply the same identification at HF, the *Bridge* is inefficient due to the two stages in the estimation. The comparison resembles the efficiency loss of the IV estimation with respect to OLS.

For nearly all cases, the *Bridge* recovers the IRFs with a smaller bias than the LF-VAR. Under few DGPs, the exception consists of the shock to the second variable y with zero impact on the first variable x . The zero restriction is imposed in the case of the HF-VAR and LF-VAR, while it is estimated from the first stage in the case of the *Bridge*. Even if the median IRF is zero, the IRFs generated by the *Bridge* across the 1000 replications may slightly differ from 0 due to finite sample bias. As a result, when the MAD is generally very low, the *Bridge* may perform worse than the LF-VAR.

While we present the main results of the Monte Carlo under averaging time aggregation in Appendix C.1, Figure 3.4 provides an intuitive portrait of the biases arising from this alternative time aggregation scheme. Even if the correct recursive structure is imposed at LF on the variance-covariance matrix of the reduced form residuals, the restriction constraints three HF periods instead of one. As a result, the LF-VAR estimates strongly biased IRFs, whereas the *Bridge* correctly recover them.

3.3.2 Time Aggregation and Misspecification

In applied research, the econometrician does not know the true DGP and, indeed, the analysis aims at recovering information on it. In this light, the interaction between temporal aggregation and misspecification deserves attention. The DGP deviates from the recursive structure which, on the contrary, is still employed as identifying restriction by HF-VAR, LF-VAR and *Bridge*. Additionally, we consider two further issues: wider frequency mismatch and measurement error.

¹²The parametrizations are reported in Appendix C.2.

3.3.2.1 Contemporaneous Effects

The impact matrix features now all non-empty entries:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} \rho & \delta_l \\ \delta_h & \rho \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & c_1 \\ c_2 & 1 \end{pmatrix} \begin{pmatrix} e_t^x \\ e_t^y \end{pmatrix} \quad (3.29)$$

We present the results under $\{c_1, c_2\} = \{-0.3, 0.1\}$, but we have tested different combinations obtaining similar results. In this case, the *Bridge* closely resembles the performance of the HF-VAR whereas the LF-VAR leads to sizable biases (Figure 3.5).

3.3.2.2 Wider Frequency Mismatch and Measurement Error

First, we now turn to a case in which the mismatch between HF and LF is significantly wider, i.e. $m = 30$, which represent the monthly-daily case. Fig. C.7 compares the identifications over the 13 DGPs through the lens of MAD. The LF-VAR induces a much larger bias with respect to the HF-VAR and *Bridge*.¹³

Second, we test the impact of measurement errors without finding any severe effect for the *Bridge*, while LF-VAR suffers the most. The results reported in Fig. C.8 refer to a case in which the first variable in the system is affected by a sizable measurement error with standard error 0.3 (30% of the actual standard deviation of the structural shocks).

3.3.3 A Practical Case - One LF and Two HF variables

Let us turn now to a more practical case: we consider a situation in which the researcher observes two HF variables and one LF variable. x is observable only at LF, whereas y and z are available at HF. We are interested in studying how the shocks to the HF variables affect x (e.g. how financial shock affect the macroeconomy). Contrary to the previous MC exercises, in the first stage of the *Bridge* we use only the two HF variables. In the second stage, we will include all three variables (time aggregated). Once again, we compare the *Bridge* with the HF-VAR (counter-factual) and LF-VAR.¹⁴

$$\begin{pmatrix} x_t \\ z_t \\ y_t \end{pmatrix} = \begin{pmatrix} \rho & \delta_{l,h_1} & \delta_{l,h_2} \\ \delta_{h_1,l} & \rho & \delta_{h_1,h_2} \\ \delta_{h_2,h_1} & \delta_{h_2,h_1} & \rho \end{pmatrix} \begin{pmatrix} x_{t-1} \\ z_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & c_{12} & c_{13} \\ c_{21} & 1 & c_{23} \\ c_{31} & c_{32} & 1 \end{pmatrix} \begin{pmatrix} e_t^z \\ e_t^z \\ e_t^y \end{pmatrix} \quad (3.30)$$

¹³Notice that the *Bridge* easily accommodates the daily-quarterly mismatch without relevant computational costs.

¹⁴In this case, we rely on the conservative identification that is described in Appendix C.1.

Again, under the many parametrization tried, we choose to present the results with

$$\begin{pmatrix} 1 & c_{12} & c_{13} \\ c_{21} & 1 & c_{23} \\ c_{31} & c_{32} & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0.65 & 0.8 \\ 0.4 & 1 & 1 \\ 0.5 & 0.8 & 1 \end{pmatrix}$$

This parametrization represents the strong simultaneity among the variables observed at HF (financial variables). The same pattern of the previous exercises emerges also in this practical case (Figure 3.6). The HF identification of the *Bridge*, not subject to temporal aggregation biases, employs only a subset of the actual information. However, the missing variable is included in the LF-VAR representation whose reduced form residuals are instrumented in the second stage of the *Bridge*. Consequently, we are using a richer information set than the LF-VAR. Moreover, economists usually assume that financial markets incorporate with a negligible lag all available information. In empirical implementations, the *Bridge* is therefore unlikely to suffer from a problem of limited information at HF.

3.3.3.1 High Frequency not High enough?

A potential concern arises if the HF identification of the *Bridge* is implemented at the wrong frequency. For example, the correct analysis for financial phenomena could be thought as intra-daily and not daily.¹⁵ To address this concern, we test whether, by relying on a HF, which is not high enough, we can still mitigate time aggregation biases. We repeat the same exercise of Section 3.3.3 but, while the HF-VAR employs the correct frequency, the *Bridge* relies on mildly time aggregated data ($m = 3$). The LF-VAR estimation is based on aggregation over nine periods ($m = 9$). Figure C.9 depicts that the *Bridge* still attenuates the biases with respect to the LF-VAR.

3.3.4 Large Systems

Until now, we have studied the performances of different identifications in small systems with ad hoc parametrizations of the DGP. However, we know that many events (shocks) hit economies at the same time and financial markets take this information nearly instantly into account. To represent this situation, we consider a nine variables VAR as DGP. Moreover, in order to tackle any possible suspicion of DGP “self-selection”, we randomly

¹⁵In case relevant data is available at intra-daily frequency, the econometrician can recover shocks at this frequency and link them with macro-variables through the *Bridge*. However, this procedure may induce noise coming from the micro-structure of the market

parametrized both the autoregressive matrix A and the impact matrix B . The only constraints that we impose ensure the stationarity of the system and a mapping between variables and shocks.¹⁶ From 100 random parametrizations of the system, we generate 1000 data-points at LF across 1000 simulations.¹⁷

We run this large experiment over three dimensions:

1. the time aggregation scheme: (a) skip-sampling
(b) averaging
2. information employed by the *Bridge*:
 - (a) partial information at LF: the HF stage of the *Bridge* employs full information but the LF stage (and LF-VAR) do not include the last two variables in the system
 - (b) full information at LF:
 - i. full information at HF: all information is included both in the HF-VAR and in the LF-VAR employed by the *Bridge*
 - ii. partial information at HF: the HF stage of the *Bridge* does not include the last two variables in the system
3. frequency mismatch: (a) quarterly-monthly ($m = 3$)
(b) monthly-daily ($m = 30$)

The case (2b) is a robustness check similar to the practical case presented in Section 3.3.3. However, we do not expect it to be particularly severe if the HF system employs financial data.

The *Bridge* improves over the performances of the LF-VAR across all the cases (Table 3.1). MAD percentage gains over the LF-VAR vary between 10% and 73%. The gains are higher when the *Bridge* employs full information and under the averaging scheme. In the latter case the biases from time aggregation are larger. Figure 3.7 displays examples of a heat-map of the MAD over the three identifications for one of the 100 systems for all combinations of shocks and variables. The similar results of the *Bridge* compared to the HF-VAR stand out immediately. At the same time, the LF-VAR produce much worse estimates than the alternative methods. Figure 3.8 presents an example of IRFs. Even in this large system, the *Bridge* performs very closely to the HF-VAR and it is subject only to a loss in precision. In conclusion, the *Bridge* greatly improves the performances of the analysis over the naive practice of time aggregation and it is often close to the performances of a

¹⁶Each shock impacts the corresponding variable more than other variables.

¹⁷Similar results hold for 500 observations at LF.

counter-factual HF-VAR. The more complete the information set is at HF in the *Bridge* identification, the closer the results of the *Bridge* to the HF-VAR. On the other hand, employing only partial information in the LF-VAR of the *Bridge* does not produce too severe losses in performances. In fact, the information omitted from the LF system does not affect the estimated B matrix but only the transmission of the shocks.

3.4 Application - Monetary Policy in the US

This section is devoted to an empirical application of our methodology. We choose a popular empirical question in order to have benchmarks for comparison: the macroeconomic effects of monetary policy shocks in the US. The related identification poses great problems due to various reasons and, in particular, due to two challenges. First, the *Federal Reserve* (FED) often changes the policy rate in response to current and expected economic conditions. Such responses cannot obviously be considered exogenous. Second, agents anticipate a large component of the changes in the policy rate (e.g. [Vicondoa \(2016\)](#)) and this anticipation can lead to VAR failures. [Romer and Romer \(2004\)](#) and [Gertler and Karadi \(2015\)](#) (RR and GK henceforth) employ two popular identification strategies and, consequently, constitute our reference points. RR mainly tackle the first challenge, analyzing US monetary policy through a narrative approach that takes into account the information contained in the Greenbook (FED forecasts). Their series of monetary shocks have been updated, among others, by [Coibion, Gorodnichenko, Kueng, and Silvia \(2012\)](#). GK focus mainly on the second identification threat, using the series of monetary policy surprise built by [Gurkaynak, Sack, and Swanson \(2005\)](#) as a proxy to reach identification in a monthly VAR. Since GK employ the Proxy-SVAR, they are the most natural comparison for the *Bridge*. [Gurkaynak, Sack, and Swanson \(2005\)](#) measure monetary policy surprises as the change in the price of Fed Funds (FF) future contracts around FOMC meetings days. While they exploit these key events for monetary policy, we do not impose a priori any special role for these dates. Nonetheless, we find ex-post that the *Bridge* identifies shocks that are abnormally sizable on FOMC meeting days *vis-à-vis* non-FOMC days. Our series of shocks produces similar macroeconomic effects to those found in [Gertler and Karadi \(2015\)](#). Moreover, the monetary policy shocks we identify are immune to some criticisms posed in the literature on [Gertler and Karadi \(2015\)](#). For example, our measure of monetary policy shock is orthogonal to changes in risk premia that may be captured by the FF futures. Finally, within our framework, we can easily decompose two components captured by GK and defined in [Gurkaynak, Sack, and Swanson \(2005\)](#) as two orthogonal factors: a “current federal funds rate target” factor and a “future path of policy” factor. The future

component is not strictly a monetary policy shock since it incorporates significant informational content. This finding is consistent with recent papers by [Campbell, Evans, Fisher, and Justiniano \(2012\)](#) and [Campbell, Fisher, Justiniano, and Melosi \(2016\)](#) who introduced the distinction between Delphic and Odyssean forward guidance.¹⁸

Instead of focusing on particular events, we estimate a daily VAR on the sample 1991m1-2008m6 to avoid any issue related with the zero lower bound. The optimal number of lags based on the three most popular information criteria is 22. Notice that we may employ more refined econometric models, suitable for financial data, ranging from a VAR featuring stochastic volatility to a SVAR-GARCH.¹⁹ Nonetheless, as we show in a few lines, a standard VAR suffices in this case. A daily analysis over such a long horizon offers vast degrees of freedom allowing us to include a large amount of variables to widen as much as possible the information set.

3.4.1 Romer & Romer and Gertler & Karadi

The Target Fed Fund Rate (TFFR) and the price of the FF Future contract 3 months ahead (FF4) constitute our monetary policy indicators. The TFFR allows us to resemble the analysis of RR while the FF4 corresponds to the analysis of GK. In the latter case, it is necessary to remove the TFFR from the HF-VAR in order to capture a mixture of shocks to the current and future path. We identify monetary policy shocks through a recursive ordering, placing our measure of monetary policy last. In other words, we regress the TFFR (FF4) on the lags and contemporaneous values of the other financial variables (plus the TFFR-FF4 own lags). This procedure orthogonalizes the reduced form residual in the TFFR (FF4) equation from all innovations in other financial variables. In this way, we ensure that we clean our measure of monetary policy shocks from other innovations in the system occurring in the same day. In an intuitive fashion, we define as monetary policy shocks the new information that enters the system at time t uniquely through our measures of monetary policy (TFFR-FF4).²⁰ We are aware that a wide literature studies the reaction of financial markets to monetary policy shocks. For example, stock prices, bond yields and exchange rates respond to the decisions of the central banks in the same

¹⁸[Lakdawala \(2016\)](#) also studies the macroeconomic effect of current and future factors. However, in our case the decomposition does not exploit FOMC meetings explicitly and it is applied directly within our daily VAR. Moreover, the current factor identified in [Lakdawala \(2016\)](#) leads to a positive reaction of CPI that we find puzzling.

¹⁹See for example [Lutkepohl and Milunovich \(2015\)](#). Additionally, when using financial variables, identification itself can exploit changes in volatility.

²⁰If the information set in our HF system is wide enough, a common unobservable factor may affect all the financial variables at the same time. The available information on macroeconomic aggregates is a good and important candidate. By ordering our monetary policy indicator last, we clean our measure of monetary policy shocks from this unobservable factor, i.e. from all available information captured by financial markets, in particular related with macroeconomic aggregates.

day. However, as explained in Section 3.2.1-3.2.3.1, the *Bridge* only requires a component of the true structural shock and not the whole structural shock to yield unbiased estimates of the impact matrix.²¹ On the other hand, a more relaxed identification scheme would incorporate other structural shocks in our measure of monetary policy shocks, violating the exclusion restriction and biasing our analysis. This issue is particularly relevant for the FF4 as the price of the FF Futures may incorporate information not strictly related with monetary policy which can nonetheless affect the conduct of monetary policy in the future.²² Notice that the procedure applied in this case corresponds to the conservative *Bridge* identification formally illustrated and tested in the Monte Carlo experiments (Appendix C.1). Our results are robust to two alternative high frequency identifications that do not rely on timing assumptions. First, we follow [Rigobon \(2003\)](#) in applying the identification through heteroskedasticity: we exploit the change in the volatility of monetary policy shocks between FOMC meeting days and non-FOMC meeting day. Second, independent component analysis allow us to identify structural shock by exploiting the non-normality of the reduced form residuals.²³

The full list of variables reads:

VAR: [*Fed Fund Future 3 months; S&P500; VXO; Bid-Cover Ratio in Treasury Auctions; Brent Crude Oil; Eurodollar Exchange Rate; Commodity Price Index; Gold Price Index; BAA Corporate Spread; FED Cleveland Financial Stress Index; Asset Backed Securities (price); 10y Treasury Spread; 5y Treasury Spread; 1y Treasury Spread, Fixed Mortgage Rate; Oil Futures; Dollar-Pound Exchange Rate; Eurodollar Futures; Target Fed Fund Rate*]

We label the shocks identified from our daily VAR as Bridge Target FFR and Bridge FF4 respectively. As a first diagnostic of our identification at HF, we study the relationship between the identified shocks and FOMC meeting days. FOMC meeting days prove to be special day for the size and volatility of the shocks *vis-à-vis* a “normal” day. Quite reasonably, such a special role is more relevant for the shorter horizon contracts, with the maximum for the TFFR. In Appendix C.4, we provide a detailed account through descriptive statistics and regression analysis.

In a second diagnostic, we compare our shocks with RR and GK by restricting our series to the FOMC meeting days only. Table 3.2 reports the contemporaneous correlation

²¹ An exogenous variation and not the whole exogenous variation with an instrumental variable terminology.

²² For the TFFR, the ordering does not matter: the correlation between shocks identified placed the TFFR last or first is 0.97, while repeating the same exercise for the FF4 the correlation falls to 0.7.

²³ Further details on these two alternative identifications are available in Section C.4.1.2 (Appendix).

across the four series of shocks during FOMC meeting days, while Table 3.3 refers to the monthly aggregates.²⁴

Notably, the Bridge TFFR shocks are highly correlated with both the RR series (0.77) and the GK series (0.41). The FF4 shocks are correlated mainly with the GK series (0.61) and less with the RR series (0.27). These correlations decrease once we move from the FOMC dates to the monthly aggregates as we consider all available days in our sample. However, the correlations remain positive and statistically significant also at the monthly frequency.

The lack of correlation around FOMC meetings between the Bridge TFFR shocks and the Bridge FF4 shocks follows by construction from the two estimations at daily frequency. When identifying shocks in the TFFR, we include the FF4 in the VAR and order the TFFR after the FF4. Consequently, a shock to the TFFR does not produce any change in the FF4 in the same day. On the other hand, our alternative identification exploits the unexpected daily changes in the FF4 (uncorrelated with the forecast errors of all other variables). As a consequence, the two series of shocks are uncorrelated.

Finally, Table C.9 reports anecdotal evidence of the largest daily shocks from our daily VAR.

We check some properties of our TFFR (FF4) series of shocks that [Ramey \(2016\)](#) and others has found problematic in GK:

- **zero mean:** we test the null hypothesis that our monthly aggregated shocks are drawn from $N(0, \sigma)$ through the Kolmogorov-Smirnov test. We cannot reject the null at any significance level (the sample mean is 0.0007 (0.0016))
- **autocorrelation:** we regress our proxy on its own previous lag and we do not find a significance coefficient. Moreover, the R^2 accounts for 0.02 (0.008)
- **predictability:** we regress our daily proxy, around FOMC meetings, on the Greenbook variables used by the RR.
 - When we perform this exercise on the TFFR shocks, we find some evidence of predictability with the private FED information. Nonetheless, the only significant coefficient related to the current level of output. In our analysis using the spot FF (FF1), this predictability vanishes and the adjusted R^2 turns negative. This discordance is most likely due to the discrete nature of the TFFR.

²⁴Figures C.17-C.18 display the comparison in monthly terms (in Appendix C.4). The predictive power of our Bridge Target for the RR shocks is reported in Figure C.19. In Figure C.20 we show that both the Bridge Target FFR and the Bridge FF4 contain relevant information to fit the GK shock series.

- For the FF4, we do not find any significant coefficient and the R^2 is in the order of 0.06, while the adjusted R^2 is negative.

This dissonance between the predictability in GK versus our series maybe due to the event-study approach of the former study. Using the change in the FF futures around a tight window might not include enough information as all the events across two FOMC meetings (and in other financial markets) are completely discarded.²⁵

The third diagnostic refers to the macroeconomic effect of monetary policy shocks: we aggregate by averaging the TFFR and FF4 shocks at monthly frequency and we use the Proxy-SVAR. Using both the shocks in FOMC meeting days only and all the monthly shocks, our results are similar to the small scale VAR of GK as reported in Figure 3.9-3.10.²⁶ If we move to the medium scale system, we find comparable results (Figure C.23).²⁷ The major difference concerns the response of the excess bond premium: the response is weaker and less persistent in our case. A possible explanation of this finding relies on the risk component. In fact, while GK take the raw change in the price of FF4 contracts, our identification cleans the proxy of the risk component by including many measures of risk in the daily VAR.

Another relevant issue is the informational (Delphic) component that GK include in their measure of monetary policy shocks. Once we include the current rate and the FF future contracts together, we are able to disentangle shocks to the current and future path of interest rates (Figure 3.11). As exemplified by the response of industrial production, a shock to the current rate produces the opposite effects to a shock to the future rate. Moreover, the IRF in GK is exactly the mean between the IRF generate by the two components. We believe that further research should disentangle Odyssean and Delphic components for a better understanding of monetary policy. However, this task goes beyond the scopes of this methodological paper.

3.5 Conclusions

Temporal aggregation is a severe issue in time series analysis, largely ignored in the macroeconomic literature. To alleviate temporal aggregation biases, this paper proposes a new methodology, the *Bridge Proxy-SVAR*, which deals with mixed frequency data. Structural shocks are recovered in high frequency systems, aggregated at the lower frequency,

²⁵These results hold both for the daily and monthly series.

²⁶In Appendix C.4, we report the same exercise that employs all the daily shocks within a month. We find very similar results.

²⁷Lunsford (2015) provides the correct critical value of the F statistic for the Proxy-SVAR and our first stage result always satisfy his criteria.

and used as a proxy for a structural shock of interest in lower frequency VARs. By instrumenting the reduced form residuals of a VAR at the macroeconomic frequency, the proxy provides identification restrictions. Our methodology relies on the superiority of identification prior to temporal aggregation over identification post temporal aggregation. In other words, our procedure exploits high frequency data for identification by controlling for the correct information set of policy makers and agents when making announcements or decisions.

The properties of the *Bridge Proxy-SVAR* are studied analytically and its performances are tested through Monte Carlo simulations. Our methodology largely outperforms a LF-VAR using temporally aggregated data, which is the common naive practice in applied macroeconomics. The *Bridge* is also close to the performances of a counter-factual HF-VAR, which constitutes the best possible estimation. In particular, if the amount of information employed is large enough, the *Bridge* replicates the estimation of a HF-VAR with lower precision. The biases introduced by temporal aggregation and the potential gain from the *Bridge* increase with the complexity of the stochastic process under examination. Unlike existing mixed frequency techniques, our methodology can exploit daily data in large dimensional systems to improve the identification of SVARs. At the same time, the MF-VAR is a different econometric model that also improves the autoregressive matrix over a LF-VAR.

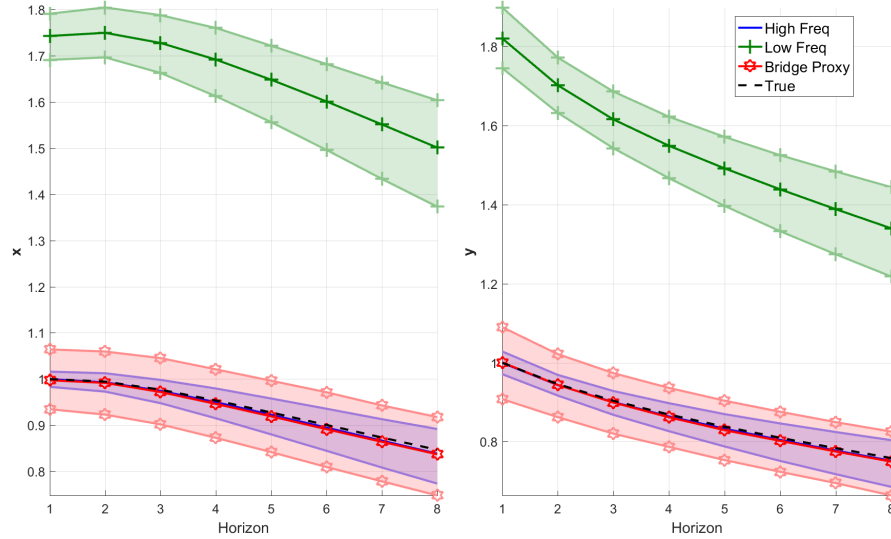
As an empirical application, we study the macroeconomic effects of monetary policy in the US. Monetary policy shocks are identified from a large scale daily VAR over the sample 1991m8-2008m6. Although we do not impose any special role for FOMC meeting days, the *Bridge* neatly captures FOMC meeting days as crucial dates. After aggregating the daily shocks at monthly frequency, we use them to instrument the reduced form residuals of the Fed Fund Rate in the monthly VAR of [Gertler and Karadi \(2015\)](#). Our analysis produces very similar IRFs to theirs. Consistently with recent findings in the literature, we show that [Gertler and Karadi \(2015\)](#) identify a mixture of shocks to the current path and future path of interest rate, where the latter includes relevant informational content.²⁸

Importantly for future research, the *Bridge Proxy-SVAR* exploits high frequency information for the identification of SVARs without relying on a definite set of events. The higher the frequency at which they are imposed, the less identifying restrictions constrain the data and the more they are likely to hold. The *Bridge* is particularly promising to improve structural analyses on macro-financial linkages, which are characterized by a wide frequency mismatch and need to take into account a wide information set.

²⁸A significant example of the potential of the *Bridge Proxy-SVAR* can be found in the companion paper [Gazzani and Vicondoa \(2016b\)](#) where we apply the methodology to identify liquidity shocks in the Italian sovereign debt market.

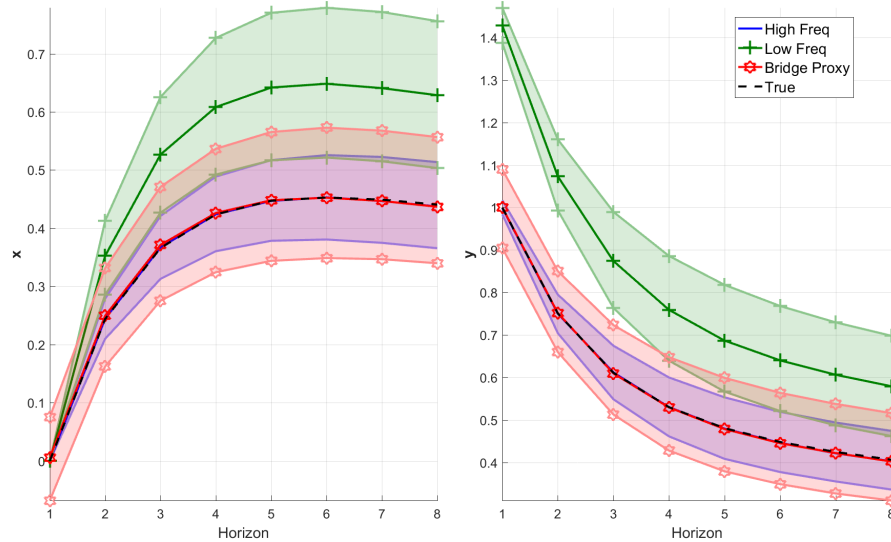
3.6 Figures and Tables

Figure 3.1: IRFs(1) in the two variable case - skip sampling



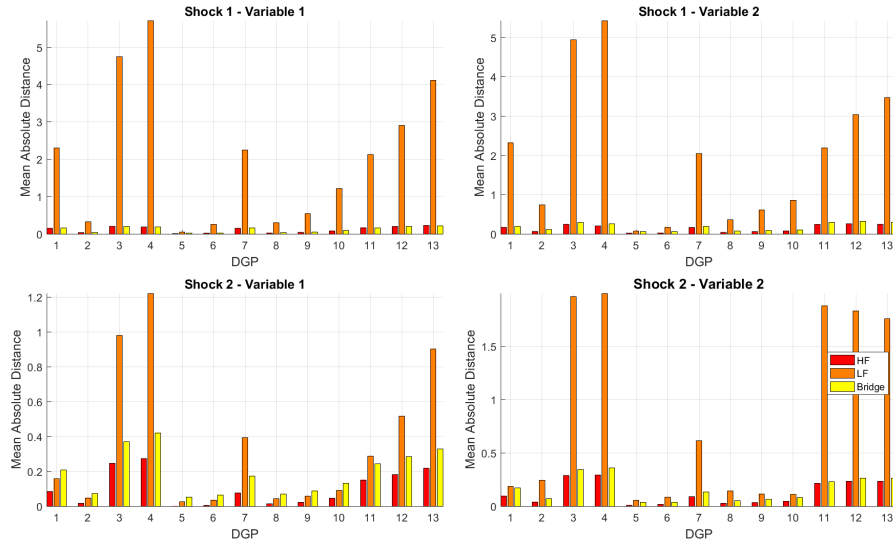
Notes: IRFs to a shock in the first variable (x) in the bivariate system. The true IRF is represented by the dotted black line. The shock is identified through the correct recursive structure in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands across 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure 3.2: IRFs(2) in the two variable case - skip sampling



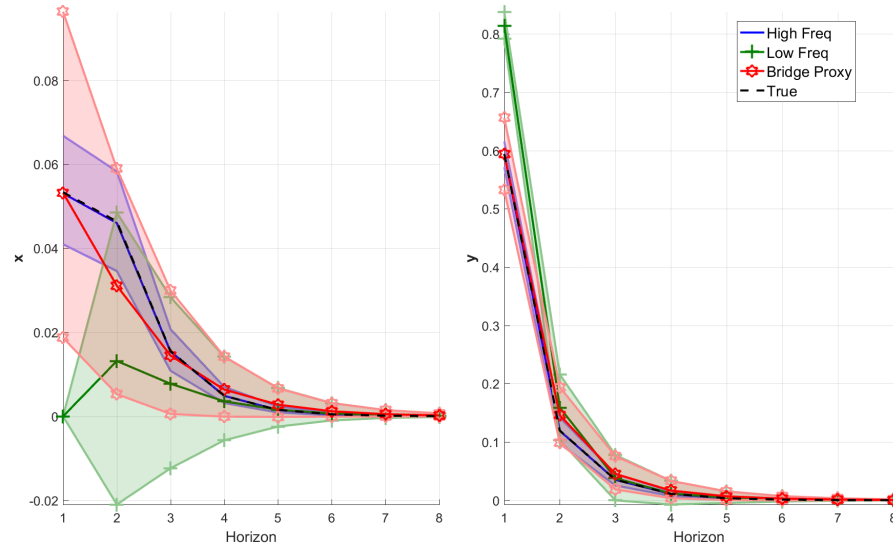
Notes: IRFs to a shock in the second variable (y) in the bivariate system. The true IRF is represented by the dotted black line. The shock is identified through the correct recursive structure in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands across 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure 3.3: MAD comparison in the two variable case - skip sampling



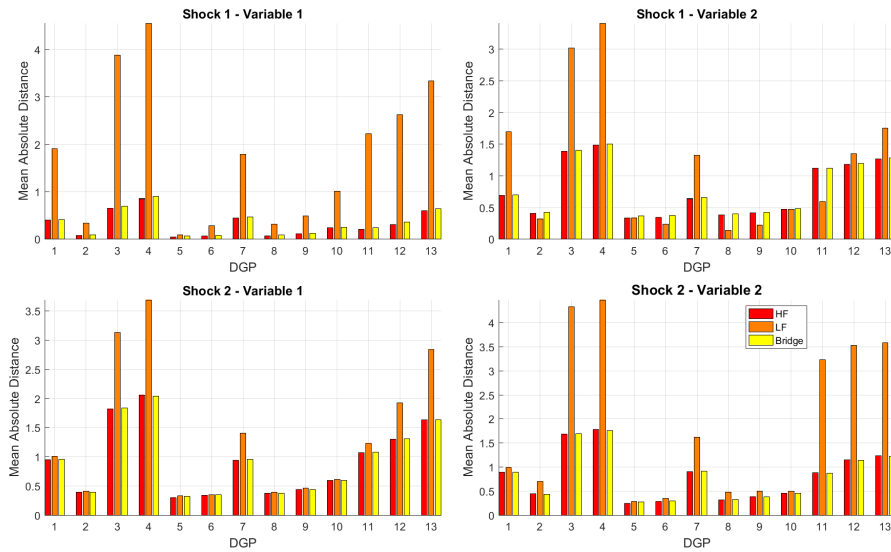
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR (through the correct recursive scheme). Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure 3.4: IRFs2 in the two variable case - averaging



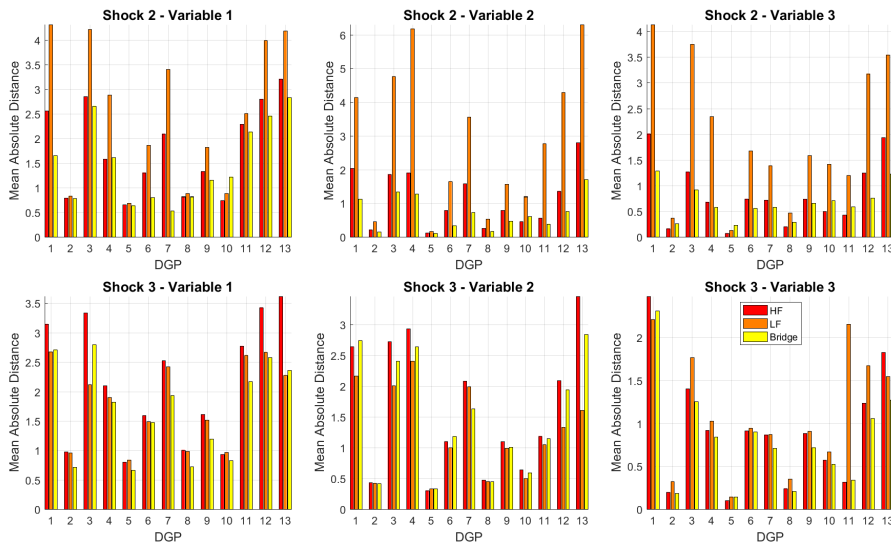
Notes: IRFs to a shock in the second variable (y) in the bivariate system. The true IRF is represented by the dotted black line. The shock is identified through the correct recursive structure in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands across 1000 replications. Time aggregation follows an averaging scheme.

Figure 3.5: MAD comparison in the two variable case - averaging



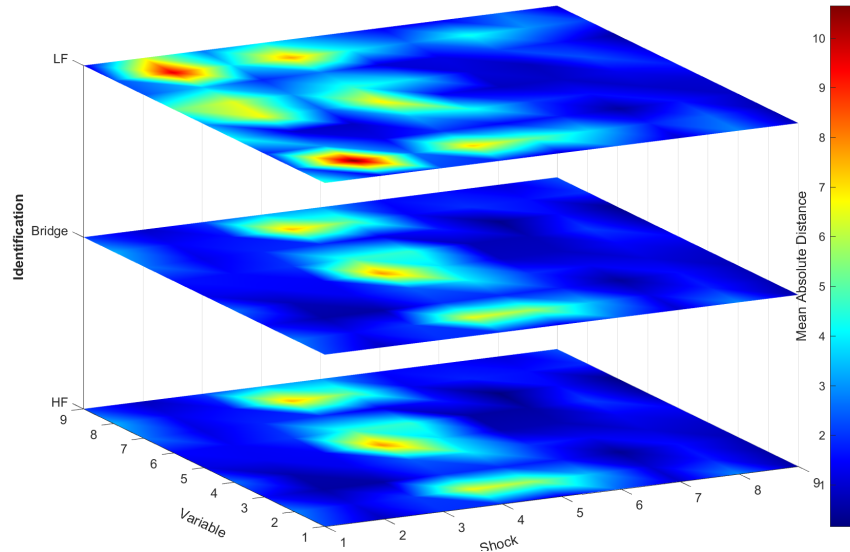
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR (through the non-correct recursive scheme). Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows an averaging scheme.

Figure 3.6: MAD comparison in the practical case



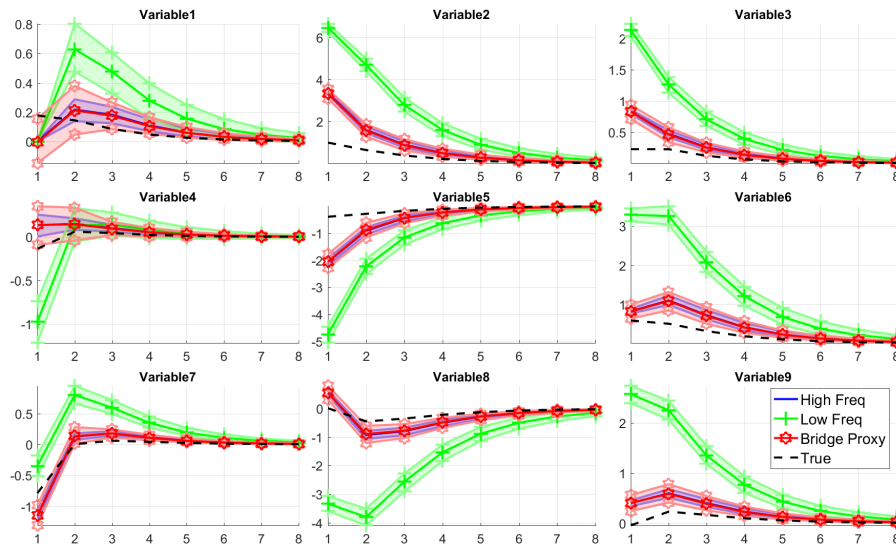
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR (through the correct recursive scheme). Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure 3.7: MAD heatmap from large randomized Monte Carlo experiment



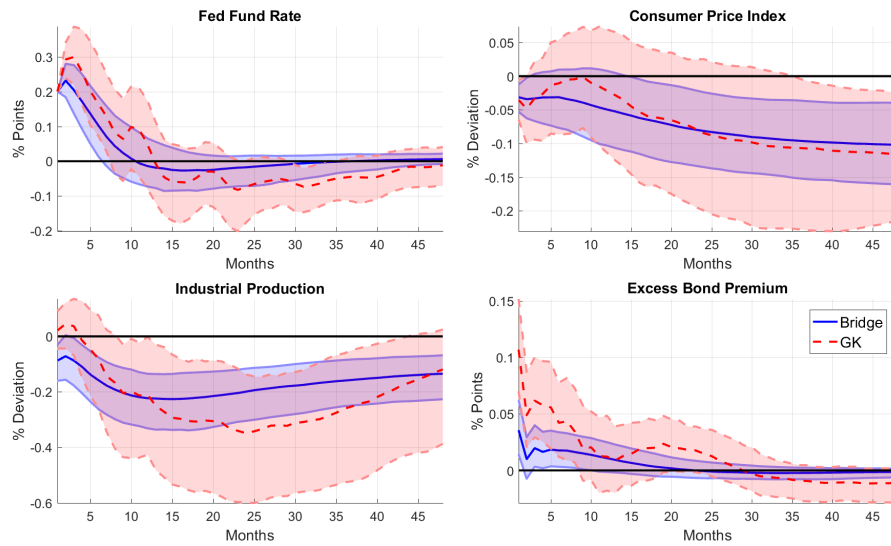
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR in one of the 100 randomly parametrized DGPs. Results are reported for each combination of shocks-variables in the system (81). The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure 3.8: IRFs from large randomized Monte Carlo experiment



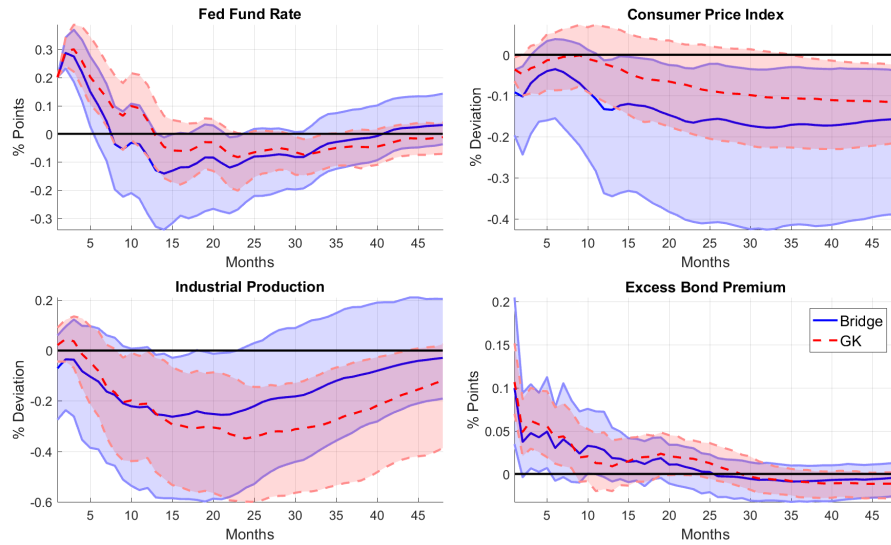
Notes: Example of the IRFs of the system to a shock in the first variable in the system, estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR in one of the 100 randomly parametrized DGPs. Shaded areas correspond to the 90% confidence bands across 1000 replications. The true IRF is represented by the dotted black line. Time aggregation follows a skip-sampling scheme.

Figure 3.9: IRFs TFFR



Notes: IRFs to a monetary policy shock identified by instrumenting the Fed Fund Rate with our series of shocks in the Target Fed Fund rate recovered from our daily VAR. From the first stage, $F - \text{stat} = 11$. The VAR includes [FFR, CPI, Industrial Production, Excess Bond Premium] and it is estimated in log-levels including the optimal number of lags (2) and a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands from 1000 replications.

Figure 3.10: IRFs FF4 comparable with Gertler and Karadi (2015)



Notes: IRFs to a monetary policy shock identified by instrumenting the Fed Fund Rate with the series of shocks in the Fed Fund Future 3 month ahead recovered from our daily VAR. We assign each FOMC meeting day only to the corresponding month (without imputing it to other months). From the first stage, $F - \text{stat} = 7.5$. We employ exactly the same specification of Gertler and Karadi (2015): the VAR includes [FFR, CPI, Industrial Production, Excess Bond Premium] and it is estimated in log-levels including 12 lags and a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands from 1000 replications.

Table 3.1: Performance comparison in Monte Carlo simulations

MAD GAINS OVER LF-VAR		
Identification	Temporal Aggregation Scheme	
	SKIP-SAMPLING	AVERAGING
Quarterly-Monthly Frequency Mismatch		
Full information at LF		
HF-VAR	21.2%	41.4%
<i>Bridge</i>	20%	36.7%
<i>Bridge</i> - Partial Information at HF	10.3%	10.8%
Partial Information at LF		
HF-VAR	32%	48.7%
<i>Bridge</i>	31.5%	28%
Monthly-Daily Frequency Mismatch		
Full information at LF		
HF-VAR	70%	81.2%
<i>Bridge</i>	65.6%	72.6%
<i>Bridge</i> - Partial Information at HF	33.2%	47.5%
Partial Information at LF		
HF-VAR	72.9%	84.7%
<i>Bridge</i>	58.7%	64%

Notes: Performance comparison across the counter-factual HF-VAR, the LF-VAR and the Bridge Proxy-SVAR. Performances are evaluated in terms of the Mean Absolute Distance (MAD) between the true IRFs and the estimated IRFs in 100 randomly parametrized DGPs. One summary statistic is computed based all the combinations of shocks-variables in the system. The gains are expressed as percentage MAD gains over the LF-VAR. We analyze different cases for a VAR(1) DGP: I) the frequency mismatch between HF and LF is 3: monthly-quarterly case. II) the frequency mismatch between HF and LF is 30: monthly-daily case. For both I) and II) we study two sub-cases: a) The Bridge employs full information at HF; b) The Bridge employs only partial information at HF (7 out of 9 variables). In this latter case, the Bridge employs the conservative identification discussed in Appendix C.1. For case a) we also analyze: a.1) the LF stage of the Bridge and the LF-VAR use all available information; a.2) the LF stage and the LF-VAR do not include all the variables in the system (only 7 out of 9 variables).

Table 3.2: Correlation across different monetary policy shocks in FOMC meeting days

	Bridge Target FFR	Bridge FF4	Romer & Romer	Gertler & Karadi
Bridge Target FFR	1	*	*	*
Bridge FF4	0	1	*	*
Romer & Romer	0.77	0.27	1	*
Gertler & Karadi	0.49	0.61	0.32	1

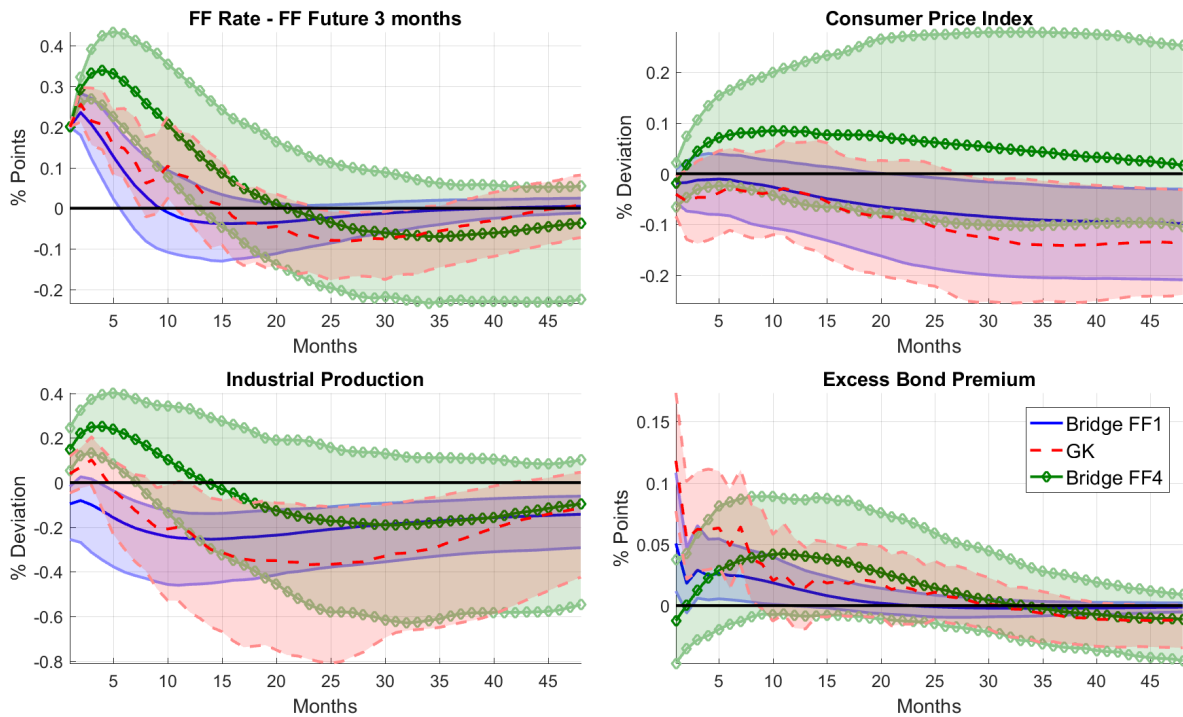
Notes: Correlations among different monetary policy shocks in FOMC meetings days: 1) Shocks to the Target FFR identified from our daily VAR; 2) Shocks to the Fed Future contracts (3 months ahead) identified from our daily VAR; 3) Monetary policy shocks as in [Romer and Romer \(2004\)](#) shocks extended by [Coibion, Gorodnichenko, Kueng, and Silvia \(2012\)](#); 4) Monetary policy shocks as in [Gertler and Karadi \(2015\)](#). All coefficients different from 0 are statistically significant at the 1% level.

Table 3.3: Correlation across different monetary policy shocks at monthly frequency

	Bridge Target FFR	Bridge FF4	Romer & Romer	Gertler & Karadi
Bridge Target FFR	1	*	*	*
Bridge FF4	0.1	1	*	*
Romer & Romer	0.34*	0.18*	1	*
Gertler & Karadi	0.27*	0.23*	0.2*	1

Notes: Correlations among monthly measures of different monetary policy shocks: 1) Shocks to the Target FFR identified from our daily VAR; 2) Shocks to the Fed Future contracts (3 months ahead) identified from our daily VAR; 3) Monetary policy shocks as in [Romer and Romer \(2004\)](#) shocks extended by [Coibion, Gorodnichenko, Kueng, and Silvia \(2012\)](#); 4) Monetary policy shocks as in [Gertler and Karadi \(2015\)](#). * denotes statistical significance at the 1% level.

Figure 3.11: IRFs - current and future path



Notes: IRFs to a monetary policy shock identified by instrumenting the Fed Fund Rate (Fed Fund Future 3 month ahead) in blue (green) with the series of shocks in the Fed Fund Future 1 (Fed Fund Future 3) month ahead recovered from our daily VAR. From the first stage, for FF1 $F - stat = 16.2$ and for FF4 $F - stat = 25.6$. The VAR includes [FFR, CPI, Industrial Production, Excess Bond Premium] and it is estimated in log-levels with the optimal number of lags (2) and includes a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands from 1000 replications.

Chapter 4

The Real Effect of Liquidity Shocks in Sovereign Debt Markets: Evidence from Italy

Joint with Andrea Gazzani

4.1 Introduction

The sovereign debt crisis has dramatically affected European countries since 2010. In particular, southern European countries like Greece, Italy, Portugal and Spain (GIPS) have been facing increasing unemployment rates and worsening credit conditions for governments, households and firms. Both the media and economic researchers have focused on the behavior of spreads in yields and credit default swaps (CDS), which are supposed to reflect default risk. However, sovereign bonds are highly demanded for their liquidity properties that have also fluctuated during the crisis.

In this paper, we examine liquidity, understood as the ease in releasing an asset quickly without incurring additional costs (i.e. market liquidity), as a different but complementary dimension of financial tensions. We measure liquidity using the *Bid-Ask Spread* (BAS) but we also employ an alternative indicator which takes into account the volumes traded in secondary markets. Government bonds are the most liquid assets in the economy, after money itself. European banks hold large amounts of these assets in their portfolio due to their historical low default risk and liquidity risk. Abrupt changes in the liquidity of sovereign bonds could affect the lending decisions of banks.

To the best of our knowledge, this is the first empirical investigation on the macroeconomic effects of exogenous changes in liquidity in sovereign debt markets, which we call *liquidity shocks*. The Euro crisis constitutes an ideal laboratory for such analysis because indicators of liquidity and default risk display different patterns that can be used for identification. Figure 4.1 shows the evolution of the *Bid-Ask Spread* (BAS), CDS and yield for Italy, which accounts for 26% of European sovereign debt, between 2004 and 2014.¹ While during 2007-2011 the yield and BAS move in opposite directions, between 2011-2012 both of them increase. Moreover, the CDS displays different dynamics with respect to the other variables. Considering the fluctuations in Italian business cycle during this period, we identify the effects and transmission channels of liquidity shocks. We base our analysis on Vector Autoregression models (VAR) and our identification strategy relies both on the standard recursive ordering and on the Proxy-SVAR methodology. The latter uses exogenous changes in liquidity identified in a financial daily VAR as an instrument for structural liquidity shocks.

Liquidity, as we show, has been a major driver for the Italian economy during the sovereign debt crisis. The Forecast Error Variance (FEV) decomposition shows that liquidity shocks explain a relevant share of the volatility of unemployment (15%) and confidence

¹European sovereign debt markets are concentrated with Italy and France accounting for roughly 50% of the total public debt. Source: European Central Bank Statistics. Italy: 26.4%, France 22.7%, and Germany 18.3%. The three variables are expressed as monthly averages.

indicators, like consumer confidence, business confidence and stock prices. A BAS shock generates macroeconomic effects that are at least as strong as the effects generated by a raise in yield spreads.²

In order to understand the transmission mechanism of liquidity shocks, we turn to survey data. The *Bank Lending Survey* and the *ISTAT Business Confidence Survey* reveal that liquidity shocks affect the lending behavior of banks through their liquidity position and costs related to their capital position. Shocks to sovereign yield spreads do not generate worse lending conditions through the same channels. Our findings are particularly relevant to improve the understanding of the relationship between real economy and financial markets.

Our empirical results can be interpreted using the theoretical framework developed by Cui and Radde (2015). They build a real DSGE model with search and matching frictions in asset markets, where the financial sector intermediates between buyers and sellers of financial assets. In this framework, an exogenous increase in financial intermediation costs affects the market participation of buyers more than the one of sellers and induces a fall in the liquidity of financial assets. Market liquidity produces relevant implications for the real economy by tightening the financial constraints of firms and reducing their financing possibilities.³ Cui and Radde (2015) mainly focus on private assets since, in the U.S., sovereign bonds did not experience a fall in liquidity during the crisis. On the contrary, as Figure 4.1 displays, in the European (Italian) case, the liquidity of sovereign bonds has fluctuated significantly.⁴ Moreover, their setup can accommodate both market-based and bank-based financial intermediation, with the latter characterizing European economies. Our empirical findings and their theoretical results are consistent in terms of: the observed fall in output, fall in consumption and investment (proxied by business and consumer confidence indicators), turnover (i.e. traded volume relative the outstanding amount of the asset), and asset prices. The only (qualitative) difference consists in their responses being starker than our IRFs because they rely on a model without nominal frictions. In a similar setup to Cui and Radde (2015), Cui (2016) studies monetary and fiscal interactions with market liquidity, and draws conclusions on optimal policies by considering government debt as provider of liquidity services.

²The joint contribution of BAS and yield spread shocks to the FEV of unemployment is 20% across 2004-2014 (15% + 5% respectively) and raises up to 30% over 2009-2014 (15% + 15% respectively).

³Notice that, contrary to the existing literature, they are able to generate the comovement between asset turnover and asset prices.

⁴Notice that we have also found similar macroeconomic results for the liquidity of corporate bonds and for the spread in liquidity between corporate and sovereign bonds. Nonetheless, in all the specifications, shocks to the liquidity of sovereign bonds induce sizeable macroeconomic effects.

Further works have also studied liquidity in theoretical frameworks: [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) and [Benigno and Nistico \(2017\)](#) study the effects of shocks to an exogenous liquidity constraint, which restricts the fraction of an asset which can be used to purchase goods. While [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) impose this constraint on the fraction of equity holdings that a household can resale, [Benigno and Nistico \(2017\)](#) restrict the fraction of government bonds that can be exchanged for goods. Unlike [Cui and Radde \(2015\)](#), these papers do not endogenize the dynamics of asset liquidity. Both papers conclude that liquidity shocks (i.e a decrease in the release fraction of these assets) produce strong and negative effects on GDP and prices, which in both cases are partially explained by a fall in private consumption. These results differ from our empirical findings since we do not find that liquidity shocks induce a significant effect on CPI inflation. [Passadore and Xu \(2014\)](#) investigate how liquidity risk and credit risk explain sovereign spreads through the optimal behavior of buyers and sellers. In an endowment economy with incomplete markets and search and matching frictions in the sovereign debt markets, they find that the liquidity component can explain up to 50% of sovereign spread during the Argentinian crisis in 2001. Although the model matches the correlations and standard deviations of consumption and net exports, they do not consider the effects on output. Overall, we contribute to this literature by characterizing the empirical effects of liquidity shocks and by identifying its transmission through the banking sector. In light of our empirical findings and of the existing models, we believe that financial intermediation and search frictions are a key feature to be taken into account when studying liquidity.

This paper is also related to the strand of the literature that analyzes the macroeconomic effects of shocks to the spread in yields. [Bahaj \(2014\)](#) and [Neri and Ropele \(2015\)](#) study the macroeconomic effects of yield shocks and find that they explain a relevant fraction of business cycle fluctuations in European countries. However, they do not consider sovereign debt liquidity in their analysis and this omitted dimension could affect their conclusions. Regarding the transmission channels, tensions in sovereign debt markets induce a tightening in credit conditions through an increase in the funding costs of banks ([De Marco \(2016\)](#)) or through the Repo market ([Boissel, Derrien, Ors, and Thesmar \(2014\)](#) and [Mancini, Ranaldo, and Wrampelmeyer \(2014\)](#)). In this paper, we show that liquidity shocks have strong macroeconomic effects and identify its transmission through the banking sector. We find that liquidity is at least as relevant as spread in yields to explain fluctuations in economic activity in Italy and Spain and that commercial banks respond to liquidity shocks in a different way than to a yield shock.

The remainder of this paper is organized as follows. Section 4.2 describes the high frequency variables that characterize Italian sovereign debt market. Section 4.3 presents the empirical specification and results using different identification schemes. Section 4.4 investigates the transmission channels by exploiting survey data. Section 4.5 compares the Italian results to France, Germany and Spain and Section 4.6 concludes.

4.2 Data Description

Sovereign debt markets can be characterized by different indicators: Spread in Yields (Spread), Credit Default Swaps (CDS), and Bid-Ask Spread (BAS). The first one captures the difference in yields that a country has to pay in order to issue sovereign debt with respect to a safe asset, which in this case is the German sovereign bond with the same maturity. CDS is a proxy for credit risk. Finally, the third is a widely-used indicator of sovereign debt liquidity (see for example [Pericoli and Taboga \(2015\)](#) and [Pelizzon, Subrahmanyam, Tomio, and Umo \(2015\)](#)).⁵ These variables enable us to characterize the sovereign debt markets. For our analysis, we use data from Italy for the period February 2004 until November 2014. The Italian sovereign debt market is one of the most important in Europe, accounting for 26% of the European government debt.⁶ Before proceeding to the analysis, we describe briefly the relationship between the three indicators. Table 4.1 displays the daily correlation between these variables, both in levels and growth rates.

CDS is highly correlated (0.91) with the Spread while the BAS displays a relative low correlation with the other two variables. This fact also holds if we consider the variables in daily growth rates instead of in levels. In particular, the daily changes of the BAS are uncorrelated with the other financial variables while CDS and Spread are positively correlated. From this preliminary description, we can see that movements in Spread are more associated with credit risk (proxied by the CDS) than liquidity risk, a similar finding with [Pericoli and Taboga \(2015\)](#).⁷ However, these variables maybe correlated with other financial ones

⁵Alternatively, people also look at the volume traded or at a combination of both. Figure A1 in Appendix D.2 displays the evolution of the volume traded together with the BAS. We use the BAS for our empirical analysis and present the results using the *Liquidity Index*, which incorporates both BAS and Turnover, in Appendix D.5.1.

⁶Source: European Central Bank Statistics.

⁷Notice that there is still no consensus in the finance literature. For example, [Schwarz \(2014\)](#) highlights, through a novel measure of liquidity, that liquidity risk explains a large share of the raising yields during the Euro crisis. [Beber, Brandt, and Kavajecz \(2009\)](#) show that, during period of market stress, investors chase liquidity and not credit quality.

like stock prices, interest rates or the equity implied volatility from options. Figure 4.2 displays the evolution of these financial variables at daily frequency.⁸

The peaks in the VSTOXX index reflect the two main periods of financial stress: the second part of 2008, associated with the collapse of Lehman Brothers, and between the second half of 2011 and 2012, related to problems in the European Sovereign Debt markets.⁹ These periods of stress are reflected in a different way for each financial variable. On the one hand, the Italian stock price index (FTSE MIB) falls with these two events and recover afterwards, without reaching the peak of 2007. The response of the Eonia rate is similar and reflects the interest rate decisions of the ECB and interbank market stress. On the other hand, financial variables associated with sovereign debt markets display different dynamics. The BAS spikes in 2009 and exhibits an abrupt change in volatility after January 14, 2011, when the *Fitch* agency downgraded Greek sovereign debt to junk status.¹⁰ The dynamics of CDS and Spread are similar during 2012, in line with the correlations reported in Table 4.1, but the Spread declines at a lower pace after the spikes than the CDS. During 2014, we observe some spikes in the BAS whereas Spread and CDS decline steadily. The key point for identification is that the six financial variables display different patterns.

Since in this paper we are going to focus on shocks to BAS, we analyze whether fluctuations in this variable are associated with particular European events. This analysis enables to us to understand better the underlying dynamics of this variable and its sources of variation. Figure 4.7 displays the dynamics of the BAS together with some key events related to the European Sovereign debt crisis, which are reported in Table D.1.

First of all, as we mentioned before, the series displays a clear change in volatility after January 14 2011. After that date, many events related to Portugal, Spain, Greece, and Italy are reflected as spikes in this variable. Additionally, other European events coincide with BAS local maxima or local minima. In particular, the BAS reached a minimum, comparable to pre-crisis levels, when Mario Draghi stated the “Whatever it takes to save the Euro”. Liquidity in the Italian sovereign debt market reflects important economic news, which is key for identification because many of those events can be considered as exogenous with respect to the Italian economy.

⁸We use the European Volatility Index (VSTOXX) instead of the one based on FTSE MIB index because it is available for the whole period and it is representative also for the Italian economy. Both indexes are highly correlated for the period when they coincide.

⁹In fact, the decline in the implied volatility happens after the famous speech of Mario Draghi, president of the ECB, on July 26 2012.

¹⁰This fact holds for Spain only a few days later.

4.3 Empirical Analysis

To analyze the effects of liquidity shocks we rely on different VAR specifications. In Section 4.3.1, we estimate a small scale VAR used to identify the effects of liquidity shocks. Then, we use an enlarged VAR for a better identification of the shocks and to characterize in higher detail the results and the transmission mechanisms (Section 4.3.2). Both specifications rely on the Cholesky decomposition to identify liquidity shocks. Given that imposing zero contemporaneous restrictions on some financial variables can be controversial, in Section 4.3.3 we employ a more agnostic identification strategy, the Proxy-SVAR, which places no restrictions on the timing or sign of the responses. Finally, in Section 4.3.4 we present extensions and additional exercises to further investigate liquidity and assess the robustness of our findings.

4.3.1 Basic Specification

As a first step, we estimate the effect of BAS shocks on Italian business cycles using a small scale VAR. In particular, we specify a VAR that includes the *Unemployment Rate*, as a proxy for economic activity; *Consumer Price Inflation* expressed as an annual rate, to capture price dynamics; *FTSE MIB*, which is the main index of Stock Prices in Italy; *Sovereign Spread*; and *BAS*. While the first two variables are useful to capture the transmission to the real economy, the last three are necessary to identify a liquidity shock. Our sample runs from February 2004 through November 2014. To deal with the different frequencies, we include the financial variables as monthly averages in order to capture all the dynamics during the period.¹¹ Following [Sims, Stock, and Watson \(1990\)](#), we estimate the model in (log-)levels by OLS, without explicitly modeling the possible cointegration relations among them.¹² In addition to a constant, we also include a deterministic trend. The lag order is selected following the three information criteria and it is always one.¹³

We identify a liquidity shock using a standard Cholesky decomposition, which is based on recursive ordering. The variables are ordered in the VAR from the most exogenous to the most endogenous, which are allowed to respond contemporaneously to all structural shocks. Thus, we order Unemployment and Inflation, assuming that they cannot react to the shock on the same month. A severe problem arises from the three financial variables that our VAR incorporates. Obviously, they always react to all the available information and so there is no convincing way of ordering them. Considering this issue, we take a

¹¹In Appendix we report summary statistic of the main financial variables aggregated at monthly frequency.

¹²[Sims, Stock, and Watson \(1990\)](#) show that if cointegration among the variables exists, the system's dynamics can be consistently estimated in a VAR in levels.

¹³We check that the residuals are normally distributed and they do not exhibit autocorrelation.

more agnostic stance. Within the financial block, we consider all the possible orderings and we report the median and percentiles of the impulse responses and Forecast Error Variance (FEV). In this way, we identify 6 rotations and, for each of those, we compute 100 bootstrap replications. Figure 4.7 displays the Impulse Response Functions (IRFs) to a one standard deviation BAS shock (i.e. a decrease in liquidity). We report the median together with 68% and 90% confidence bands that include both the identification (from the different Cholesky orderings) and statistical uncertainty.

An increase in the BAS induces an increase in Unemployment which lasts 10 months and a slight decrease in CPI inflation. However, the remaining financial variables do not react to the BAS shock. Similar results hold if we estimate the same VAR using the pre-2009 and the crisis sample.¹⁴ Thus, shocks to the BAS have strong effects on economic activity. In order to understand the channels behind this relationship and to see whether results are robust, in the next section we consider a large scale VAR.

4.3.2 Full Specification

We aim at assessing the macroeconomic effects of BAS shocks, with special emphasis on the comparison with other financial shocks. For this purpose, we enlarge the previous VAR system with other variables. This system features six macroeconomic variables (Unemployment, CPI Inflation, Public Debt, ECB Repo, Italian M2, Consumer and Business Confidence) plus five financial indicators (stock prices, Spread, CDS, BAS and VSTOXX). This set of variables is necessary to identify financial shocks and assess their transmission to the real economy.¹⁵ Like in Section 4.3.1, we identify the liquidity shock through recursive ordering. In particular, we assume that macroeconomic variables cannot react contemporaneously to the financial shocks and we order them as follows: [UNEMPLOYMENT, CPI, PUBLIC DEBT, M2, CONSUMER CONFIDENCE, BUSINESS CONFIDENCE].

Again, within the financial block, we consider all the possible orderings (120 rotations), compute five bootstrap replications for each of them and report the median and percentiles of the impulse responses and FEV. Different possible orderings across the financial block lead to very similar results, which means that the covariance matrix of the reduce form residuals is close to a diagonal matrix.

Figure 4.5 displays the IRFs to a one standard deviation BAS shock, where 68% and 90% confidence bands include both the identification (from the different Cholesky orderings)

¹⁴For ease of exposition, we present these results in the Appendix.

¹⁵As in Section 4.3.1, we estimate the VAR in (log) levels by OLS equation by equation. The optimal number of lags is one. Our sample consists of 130 observations which leaves us with enough degrees of freedom for the estimation (15 coefficients in each equation).

and statistical uncertainty. A negative liquidity shock induces an increase in unemployment that reaches its maximum after four months without a significant effect on inflation, comparable to the findings of the VAR presented in Section 4.3.1. The stock of government debt falls with a lag whereas there is no reaction in the Repo rate and M2. Both business and consumer confidence indicators decline in response to the shock and reach their trough four months after the shock. The response of confidence is strong across all the specifications and could reflect a fall both in current and future consumption, which may help to explain the strong response of unemployment (Ludvigson (2004)). Moreover, these dynamics are consistent with the findings of Garcia and Gimeno (2014) for flight-to-liquidity episodes. The FEV contributions of BAS to consumer confidence, business confidence and stock prices are respectively 15%, 9% and 7% one year after the shock. Moving to the financial block, the equity premium, CDS and spread increase and the FTSE declines by 1%, all of them with a lag. Responses of financial variables are in line expected movements: a decrease in the BAS, which could be interpreted as an increase in the uncertainty regarding the value of the underlying asset, reduces prices (i.e. increases the Yield), confidence, and stock prices and increases volatility and CDS.

A key point in our analysis, in light of the outstanding literature on the Euro Crisis, consists of the comparison between BAS (Figure 4.5) and Spread shocks (Figure 4.6). The Spread shock induces a similar effect on unemployment slightly less persistent and significant. However, this shock has a negative effect on CPI inflation, which declines by 0.04% points 2 months after the shock. Even if the response of CPI inflation is different with respect to a BAS shock, in Section 4.3.3 we show that, by using the Proxy-SVAR, the IRF of CPI to a BAS shock is also negative.¹⁶ Unlike in the previous case, consumer confidence and business confidence do not display a significant reaction. Regarding the financial block, the responses are similar in magnitude (even if less significant) but less lagged than the case of a BAS shock. An increase in Spread induces a delayed raise in BAS. While the effects on unemployment are similar to the ones reported by Neri and Ropele (2015) using a similar sample, the ones on inflation are the opposite from theirs. This difference may be due to the omission of the liquidity dimension.

For a more comprehensive comparison among financial shocks, in Figure 4.7 we report the FEV decomposition of unemployment (i.e. how much each financial shock explains of unemployment's volatility). BAS shocks explain approximately 15% of unemployment fluctuations at a two year horizon. The second largest shock in relevance is the stock prices, accounting for 7%. The remaining financial shocks do not explain a significant fraction of

¹⁶As we show later on, CPI is the only variable whose dynamics changes across the two methodologies. Notice that this difference comes from the years 2004-2009 as we display in Figure A2. The response of Spread is robust for the sub-sample 2009-2014.

fluctuations in unemployment. All in all, exogenous fluctuations in financial variables explain around 30% of the total variability of unemployment. From this analysis, we can conclude that liquidity is a major driver of unemployment, out of all the financial variables, for the period under analysis.¹⁷

4.3.3 Proxy-SVAR

While the results of Section 4.3.2 are robust to the different Cholesky orderings, still, in each rotation, we are constraining (some) financial variables not to react on impact to other financial shocks. In this section, we relax this assumption by applying the so called *Proxy-SVAR* identification developed by [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#). The main idea is to use information external to the VAR system as a proxy for the structural shock of interest, the BAS shock in our case. In practice, the proxy constitutes an instrument for the reduced form residuals of the VAR and provides partial identification of the structural shocks. The instrument is assumed to be correlated with the structural shock of interest but not with the remaining ones. An advantage of this technique is that, as long as the proxy is a relevant and valid instrument, the identification relies on a much weaker set of assumptions than the recursive identification scheme.¹⁸ In other words, no assumptions are made on the contemporaneous relationship among the variables in the system. Appendix D.4 contains a detailed explanation of this methodology.

In order to obtain a valid instrument for BAS, we propose a new way to identify the proxy for the Proxy-SVAR at high frequency. We label this identification “*Bridge Proxy-SVAR*” because the Proxy-SVAR links two VAR systems that include data at different frequencies. In [Gazzani and Vicondoa \(2016a\)](#), we illustrate analytically the properties of *Bridge Proxy-SVAR* and test it via Monte Carlo simulations. The procedure consists of the following steps:

1. Construct two VARs systems. The first one is a VAR that incorporates daily financial variables relevant for the analysis, defined as High Frequency VAR (HF-VAR). This VAR features [*BAS*, *CDS*, *Yield*, *FTSE*, *Eonia*, *VIX*]. The second one is a VAR, defined as Low Frequency VAR (LF-VAR), that includes variables at monthly frequency. In particular, it is the same system that we define in Section 4.3.2. Again, the financial variables in the LF-VAR are included as monthly averages.

¹⁷The relative contribution of each financial shock changes if we consider the sub-sample 2009-2014 (Figure A3 in Appendix D.5). In this case, the contribution of spread is similar to the one of BAS, which is quantitatively stable over the full sample.

¹⁸The proxy is not assumed to be perfectly correlated with the structural shock, but only to be a component of it.

2. Estimate the HF-VAR and identify the structural shock of interest ε_{HF}^{BAS} with the most appropriate identification scheme. Given that economic theory does not support identification via sign restrictions, we apply the recursive ordering Cholesky decomposition. Notice that the biases implied by Cholesky in the HF-VAR are much lighter than in the LF-VAR. Since we observe a structural break in the daily volatility of financial variables in 2009, we estimate a VAR at daily frequency to identify structural innovations in the BAS during the period 2009m1-2014m11 and we use them as an instrument for the structural BAS shocks at monthly frequency.
3. Aggregate ε_{HF}^{BAS} into monthly frequency obtaining $\bar{\varepsilon}_{HF}^{BAS}$.
4. Estimate the LF-VAR and apply the Proxy-SVAR identification, where $\bar{\varepsilon}_{HF}^{BAS}$ is employed as a proxy for the structural shock of interest in the LF-VAR ε_{LF}^{BAS} . Namely, the reduced form residual u_{LF}^{BAS} is instrumented with $\bar{\varepsilon}_{HF}^{BAS}$. Again, the underlying assumptions concern the relevance, $corr(\bar{\varepsilon}_{HF}^{BAS}, \varepsilon_{LF}^{BAS}) \neq 0$, and the validity, $corr(\bar{\varepsilon}_{HF}^{BAS}, \varepsilon_{LF}^j) = 0 \quad \forall j \neq BAS$, of the instrument.

This proxy explains a significant fraction of BAS reduced form residuals from the monthly VAR. The statistics of the first stage are $F\text{-stat} = 29.465$ and $R^2 = 0.30231$, which satisfies the requirements of a strong instrument suggested by [Stock and Yogo \(2002\)](#). This means that a relevant fraction of the reduced form residuals are explained by the daily shocks to the BAS.¹⁹ Figure 7 reports the IRFs to an instrumented shock to the BAS. The BAS shock induces a significant and persistent effect on unemployment, very similar both quantitatively and qualitatively to the ones described in Section 4.3.2. Unlike with the recursive ordering, CPI inflation decreases by 0.02% after the shock. As displayed in Figure A2, this difference is not due to the methodology but to the shorter sample used. The remaining variables in the macroeconomic block display a comparable reaction to the recursive ordering case. In particular, the BAS shock generates a strong response in the indicators of confidence. All the financial variables display a significant lagged response, except for the Equity Premium that reacts on impact.

Even if the Proxy-SVAR relies on a weaker set of assumptions, we include it only as an alternative because this approach just reaches partial identification. This implies that we cannot explicitly compare liquidity and spread shocks. Nonetheless, the results from the Proxy-SVAR confirm the validity of the recursive ordering identification previously applied, that is the standard methodology. Notice that, with the Proxy-SVAR, even without imposing any contemporaneous restriction, financial variables do not display a significant

¹⁹Figure 8 in Appendix D.4 includes a figure with the first stage results.

response on impact (apart from the Equity Premium). However, under this methodology, we can still compute the historical contribution of liquidity shocks to unemployment, which help us to assess the relevance of these shocks during the recent crisis. In fact, Figure 4.7 provides the historical interpretation of our results by displaying the component of unemployment explained by the BAS. In the upper panel, unemployment is expressed in deviation from the trend whereas, in the lower one, at the business cycle frequency.

The BAS explains the initial increase of unemployment, with respect to its trend, in 2010 and 2013 and also the reduction observed in 2014. Finally, it is also relevant to explain the increase observed during the last stage of 2014. Similar conclusions hold if we look the contribution at business cycle frequencies.

Our findings, which are robust across the two different identification strategies, suggest that liquidity shocks have significant effects on unemployment. These results also hold if we consider industrial production and the *ITA-coin*.²⁰ A question that may arise naturally is why this peculiar financial variable, not even on the focus of media's attention, has so strong real effects. First, we find that all the measures of confidence decline significantly in response to the decrease in liquidity. This could point to a decrease in aggregate demand that explains the decrease in economic activity (Ludvigson (2004)). Second, in Section 4.4, we show that commercial banks change their lending conditions in response to liquidity shocks.

4.3.4 Alternative VAR Specifications

Shocks to the BAS are a major driver of unemployment for the period under analysis. In this subsection, we consider additional specifications to assess the robustness of our findings. For the ease of exposition, the IRFs of the exercises performed in this section are presented in the Appendix D.5.

4.3.4.1 Indicator of Liquidity

The BAS is one of the most popular indicators of liquidity. However, it captures only the price dimension of liquidity while another relevant feature is the quantity side. A fall in liquidity equally distributed across price and quantities would generate an increase in the BAS and a fall in the quantity traded. In order to explore whether this relationship holds in our analysis, we estimate the Full VAR including the Turnover, volume traded normalized by the stock of the outstanding asset, as an additional variable in the system. While responses of macroeconomic variables to a BAS shock remain unchanged, the turnover

²⁰Appendix D.5 displays the IRFs using each indicator.

displays a significant reduction. This result conforms with the theoretical predictions of the model proposed by Cui and Radde (2015).

In order to explicitly take this double dimension of liquidity into account, we compute a liquidity index indicator that is defined as the ratio between the Turnover and the BAS.²¹ Thus, when the liquidity index is higher (lower), the asset can be considered more (less) liquid. We estimate the same baseline VAR but replacing the BAS with the Liquidity Index. Both responses of variables in the system and the contribution of liquidity to explain fluctuations in unemployment remain practically unchanged.

4.3.4.2 Measures of Economic Activity

All the results presented so far rely on Unemployment as a proxy for economic activity. Alternatively, we estimate the VAR including Industrial Production and a Coincident Indicator of Economic Activity (*Indicatore Ciclico Coincidente (ITA-coin)*), a monthly indicator of economic activity published by the Bank of Italy.²² Results are comparable with the ones using Unemployment.

4.3.4.3 Different Samples

Figure 4.2 shows that financial variables display a change in volatility at daily frequency after 2009. Moreover, in the same window there is also a stark fall in interest rates that can constitute another source of structural break. To see whether this fact affects our findings, we estimate our baseline VAR for the sub-sample 2009-2014. The main results remain unchanged. To tackle the possibility that our results are driven only by the Euro crisis, we run the same analysis in 4.3.1 over the sample 2004-2009. Once again, we find very similar results in this short sample.

4.3.4.4 Corporate Liquidity

The finance literature has reported sizable fluctuations of the market liquidity of corporate bonds in the U.S during the financial crisis (see Dick-Nielsen, Feldhutter, and Lando (2012)). Even if Italian firms rely more on banks as a source of finance, we analyze the interrelation between sovereign and corporate liquidity. For this aim, we use the BAS of a

²¹The correct measure would employ the quantity bid and asked, but unfortunately we cannot access this data. Therefore, we use the actual number of trades (turnover on the secondary market) compiled by MTS.

²²See <https://www.bancaditalia.it/statistiche/tematiche/indicatori/indicatore-ciclico-coincidente/> for more information about *ITA-coin*.

representative corporate bond and include it in the VAR instead of the Equity Premium.²³ A couple of interesting facts emerge. First, the effects of sovereign BAS shocks remain unchanged. Second, an exogenous increase in the private BAS generates a significant effect on Unemployment, which is comparable to the one induced by the sovereign BAS. Finally, an exogenous change in the private BAS does not affect significantly the sovereign BAS. These findings suggest that both BAS are relevant to explain economic activity. Finally, we also consider the BAS as a spread between the corporate and sovereign. A shock to this spread induces also sizable effects on economic activity.

4.3.4.5 Market Stress Index

As we show in Figure 4.7, the BAS reflects some relevant European events, which may be regarded as periods of Market Stress. To assess potential omitted variable biases, we replace the Equity Premium with the *Composite Indicator of Systemic Stress* (computed by the ECB) in our VAR. IRFs are comparable with respect to the baseline specification. Thus, these results confirm that our results are not biased by omitting other measures of stress in financial markets.

4.3.4.6 Financial Volatility

Financial variables display a time varying volatility at high frequency which is not reflected at monthly frequency. To control for these changes, we compute the monthly volatility of BAS, CDS and Spread using daily data. We build the first principal component that explains 78% of the variability of these three measures. Then, we include this index in the VAR instead of the Equity Premium. The IRFs and the FEV are unaffected. This suggests that previous findings are not driven by changes in volatility.

4.4 Transmission Channels

The easiness of trading sovereign bonds is particularly relevant for Italian banks because they hold exceptional amounts of Italian sovereign debt. [Gennaioli, Martin, and Rossi \(2014\)](#) show that banks hold large amounts of public bonds due to their liquidity properties. The *European Stress Test* carried out in 2010 provides some insights on the amount of these assets held by the main Italian commercial banks: Banca Popolare, Intesa San Paolo, Monte dei Paschi, UBI Banca and Unicredit. Italian banks' holding of national securities

²³We use the BAS of a bond issue by Telecom (*TELECOM ITALIA TITIM 5 3/8 01/19*) which is the longest series available. Moreover, it is highly correlated with the liquidity of the other bonds (e.g. 0,91 with Unicredit - *UCGIM 4 3/8 01/20* and 0,65 with ENI - *ENI INTERNATIONAL FINANCE ENIIM 5 1/27/19*. Source: Bloomberg.

accounts for 74% of their total government bond holdings. This share is even higher if we consider only the trading book: 84%.²⁴ Moreover, Italian sovereign bonds constitute 6.13% of the total assets owned by those five Italian banks (Gennaioli, Martin, and Rossi (2014)). In this Section, we assess whether and how changes in sovereign debt liquidity and spread affect banks' lending decisions using two official surveys. First, we employ the *ISTAT Business Confidence Survey*, which is carried out at monthly frequency. Second, we use the *Bank Lending Survey* from the Bank of Italy, which is available at quarterly frequency. Unlike statistics about total amount of loans that include both demand and supply effects, survey data allows us to disentangle more precisely the transmission channels.

4.4.1 ISTAT Business Confidence Survey

We employ data from the *ISTAT Business Confidence Survey* to assess the effects of liquidity and spread shocks on firms' credit conditions. This survey, which is carried out by ISTAT at a monthly frequency since March 2008, covers a representative sample of 4,000 firms in the manufacturing sector and includes information about firms' assessments and expectations on the Italian economic situation.²⁵ To assess how changes in sovereign debt liquidity and spread affect the credit market, we focus on questions regarding credit supply and demand and include them as an additional variable in our baseline VAR.²⁶ Given that the sample is shorter, we estimate the baseline VAR described in section 4.3.2 since August 2009, when all the variables are available, including one variable at the time to avoid losing degrees of freedom. In particular, we assume that credit decisions cannot react on impact to financial shocks and place these credit variables before the consumer confidence, business confidence and the financial block.²⁷ Figure 4.10 displays the IRFs to a liquidity deterioration and a positive sovereign spread shock.

Liquidity and sovereign spread shocks have different effects on the credit market. On the one hand, a BAS shock (i.e. a decrease of liquidity) does not change the index on perceived credit conditions but induces worse conditions in terms of interest rate, size of the credit, and costs other than the interest rate. Moreover, the BAS leads to an rise in the number of denied loans by banks with a lag. On the other hand, a spread shock immediately reduces the credit access and increases the number of denied loans by banks

²⁴For regulatory purposes, banks divide their activities into two main categories: banking and trading. The trading book was devised to house market-related assets rather than traditional banking activities. Trading book assets are supposed to be highly liquid and easy to trade.

²⁵See <http://siqua.istat.it/SIQual/visualizza.do?id=8888945&refresh=true&language=UK> for a detailed description of this survey. There is an analogous survey for the service sector but the sample is shorter. However, results are similar to the ones reported in this section.

²⁶The Appendix contains the questions that we consider from the ISTAT Business Confidence Survey.

²⁷Results remain unchanged if we place this variable last in the VAR.

and a rise in the interest rate charged by banks. Notably, the reason why credit is not obtained by firms (*credit not obtained*) is not related with firms rejecting the loans offered by the banks (*credit not obtained - too heavy conditions*), but due to banks denying the loan (*credit not obtained - bank denial*). In other words, credit supply is driving the lower access to credit. While the spread shock affects mostly the interest rate and the size of the credit, a liquidity shock also induces higher costs (apart from the interest rate). These higher costs reflect higher commissions, extra-costs and tighter deadlines. For what concerns the timing, we observe a more lagged response to a liquidity shock than to a spread one. This is consistent with the delayed response of financial variables presented in Section 4.3.3.

After analyzing firm's survey responses, in the next subsection we assess whether these results are consistent with bank's replies. Additionally, we investigate the reasons that drive banks behavior.

4.4.2 Bank Lending Survey

We exploit the *Bank Lending Survey* (BLS) on Italian commercial banks to determine the effects of liquidity and spread shocks. This survey, which is carried out by *Banca d'Italia* in collaboration with the *European Central Bank* at quarterly frequency since January 2003, contains very detailed information about bank's decisions on different dimensions.²⁸ Unlike in the previous subsection, we cannot include the replies to the survey in the baseline VAR due to the differences in frequencies. For this reason, we aggregate the monthly BAS and spread shocks identified in section 4.3.2 to quarterly frequency and estimate the following equation:

$$\Delta BLS_t^i = \alpha + \sum_{j=1}^8 \delta_j \Delta BLS_{t-j}^i + \sum_{j=0}^{12} \beta_j shock_{t-j}^k \quad (4.1)$$

where ΔBLS_t^i , $shock_t^k$ denote the change in bank's behavior and quarterly BAS and spread shocks, respectively. We follow [Romer and Romer \(2004\)](#) and choose eight lags for the autoregressive part and twelve for the effect of the shock. Then, we compute the IRF to a BAS and spread shock for the main bank decisions available in the Survey (Figure 4.7).²⁹

Banks increase their credit standards to firms in response to liquidity and spread shocks with a similar magnitude. However, the reasons for increasing standards differ. On the one hand, in response to negative liquidity shock, banks react due to changes in their liquidity position and costs related to their capital position. On the other hand, banks do not report changes in the relevance of the asset and liquidity position in response to a

²⁸ More information about this survey can be found at [BLS](#).

²⁹ The Data Appendix contains the detailed questions we consider from the Bank and Lending Survey.

spread shock. These differences in behavior suggest that banks increase their focus on their own balance sheet in case of a liquidity deterioration in sovereign debt markets. Moreover, banks adjust immediately their standards for mortgage loans while they do not change it for the case of spread shocks. Mortgages are collateralized loans and, in case of no repayment and liquidity problems, banks may not find it easy to release the house and that may explain why they increase their standards. Finally, both shocks are associated with an increase of similar magnitude in the perception of risk about economic activity.

With the evidence presented in Sections 4.3 and 4.4, we conclude that liquidity shocks have relevant real effects on the Italian economy and we document that transmission is through changes in the credit supply. In the next section, we analyze whether liquidity shocks are also relevant for the other three major Eurozone economies: Germany, France, and Spain.

4.5 Comparison with other European Countries

In order to assess whether liquidity shocks are also relevant drivers of the business cycle in other European economies, we perform the previous analysis also for Germany, France, and Spain. First, in Table 4.2 we analyze if sovereign BAS are correlated across countries, which would indicate to what extent they are explained by common shocks. We observe that BASs are positively correlated across the biggest four Eurozone economies. While BAS for Germany seems to be less correlated with the rest of the countries, the correlation is stronger between France, Italy and Spain.

Second, we estimate the baseline VAR described in Section 4.3.2 for each country to determine whether the macroeconomic results for Italy also hold for the other countries.³⁰ A first relevant finding is that the identified BAS shocks are positively correlated across countries: the correlation ranges from 0.3, France-Germany, to 0.21, France-Italy.³¹ Both the correlation of the variables in levels and of the shocks indicate that liquidity in sovereign markets is driven by a relevant European component.

We present the macroeconomic relevance of the financial shocks, across the four countries, in Figure 11 through the FEV decomposition of unemployment. There is a clear heterogeneity between the Mediterranean countries and the central European ones. On the one hand, changes in BAS are an important driver of unemployment for Spain and

³⁰The sample is February 2004–November 2014 for Germany, Italy and Spain. Due to the lack of CDS data before 2005, the sample for France starts in August 2005. All financial variables are expressed as monthly averages.

³¹In particular, the estimated cross-country correlations are statistically significant for all the cases but between France and Spain.

Italy. For both cases, BAS shocks account for 15% of unemployment fluctuations.³² A special feature of Spain is the relevance of CDS, which might be due to the perceived higher default risk. On the other hand, exogenous fluctuations in stock markets are the most relevant source of unemployment fluctuations for Germany and France. In fact, neither BAS nor sovereign spread seem to be relevant to explain unemployment fluctuations in these countries. Even if financial shocks explain a similar fraction of the total variability of unemployment (around 30%), the relevance of each financial shock differs across countries. Although the sources of this difference are beyond the scope of this paper, one possible reason could be the lower tensions in sovereign debt markets in France and Germany. Moreover, while Italian and Spanish banks are heavily exposed to their national sovereign debt (around 75% in 2010 according to the European Stress Test), French and German financial institutions hold a more diversified portfolio.

4.6 Conclusions

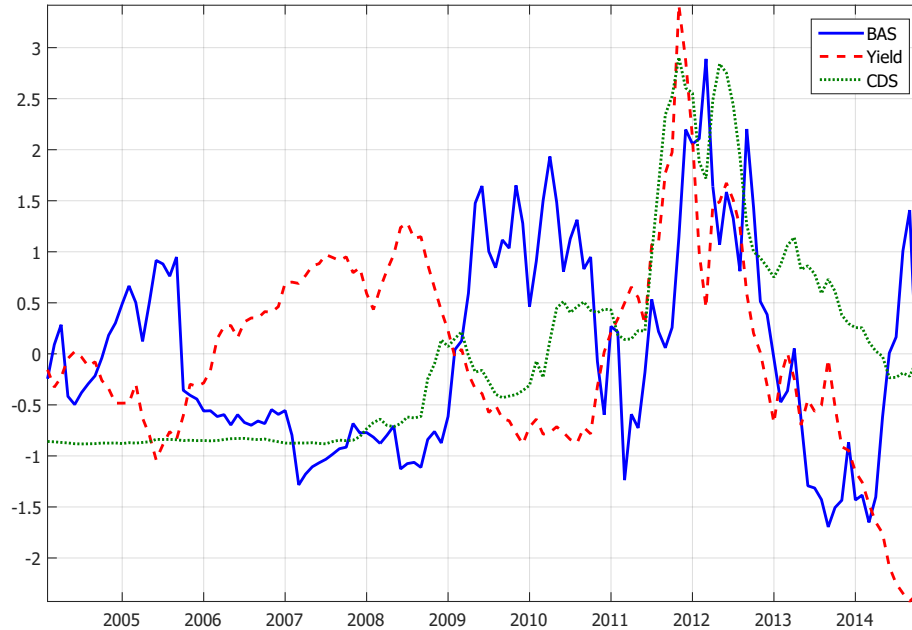
Economists have been focusing on sovereign debt markets due the European Sovereign Debt Crisis. Contrary to the growing number of theoretical models that analyze changes in liquidity in those markets, the empirical evidence on their real effects is still null. In this paper, we provide novel empirical evidence on the macroeconomic effects of changes in liquidity in secondary sovereign debt markets. We focus on the Italian economy that was hit both by credit risk and liquidity shocks during the recent crisis. We use monthly data from 2004 to 2014 in a VAR analysis and consider two alternative identification strategies: recursive ordering and the Proxy-SVAR, which yield consistent results. The former takes into account all the possible orderings among financial variables. The Proxy-SVAR exploits a daily financial VAR to control for all high-frequency changes in financial markets. Specifically, we use daily BAS structural shocks as proxy for the monthly BAS structural shocks. We find that, contrary to popular perceptions, liquidity is a major financial driver of economic activity. An exogenous raise in this variable generates a strong (15% of the Forecast Error Variance) and persistent (10 months) surge in unemployment. The other variables that are mostly affected are confidence indicators as Stock Prices, and Consumer and Business Sentiment. Banks and firms survey data reveal that liquidity shocks have significant effects on banks standard, in terms of loan's size and through additional costs, particularly due to the asset and liquidity position of Italian banks. Similar macroeconomic effects hold for Spain, whereas liquidity shocks are not a significant driver for France and Germany.

³²Moreover, the IRF to a BAS shock has similar effects both in terms of magnitude and persistence.

Our results differ from existing models, as [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) and [Benigno and Nistico \(2017\)](#), where liquidity shocks induce a pronounced deflation. Therefore, in particular in the light of our findings related to the banking channel, we believe that models that focus on the asset and liquidity position of financial intermediaries can enhance our understanding of these phenomena. We regard [Cui and Radde \(2015\)](#) as a first step towards this interesting direction for future research. Frameworks of this kind, which can generate macroeconomic effects consistent with the empirical evidence, can be used to assess whether and how policy makers should react to changes in liquidity ([Cui \(2016\)](#)). They mainly focus on the liquidity of corporate bonds as their reference is the US economy. Instead, by studying European economies we conclude that the liquidity of sovereign bonds is a key financial dimension for the business cycle. Liquidity shocks to these two different assets may involve diverse policy reactions and have different implications.

4.7 Figures and Tables

Figure 4.1: Key Financial Variables



Notes: Italian (standardized) BAS, CDS and Yield (monthly average). Each variable corresponds to the first principal components of 2, 5, 10 years bond maturities. Source: Bloomberg (BAS) and Banca d'Italia.

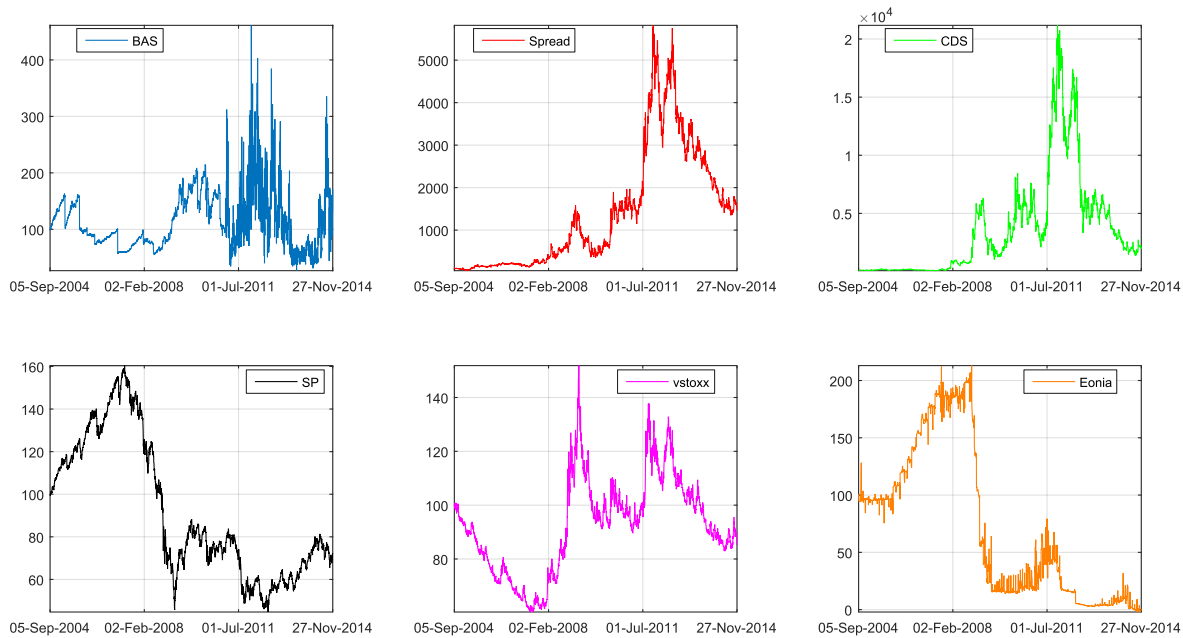
Table 4.1: Contemporaneous Correlation between Financial Variables

Levels	BAS	Spread	CDS
BAS	1	0.24***	0.36***
Spread	0.24***	1	0.91***
CDS	0.36***	0.91***	1

Growth Rates	BAS	Spread	CDS
BAS	1	-0.03	-0.03
Spread	-0.03	1	0.23
CDS	-0.03	0.23***	1

Notes: Contemporaneous daily correlation between Italian financial variables at daily frequency: BAS, Spread, CDS. All the variables correspond to 2 years maturity. Left-panel in levels, right-panel in growth rates. ***, **, * denote 99%, 95% and 90% confidence intervals.

Figure 4.2: Daily Dynamics of the Main Financial Variables



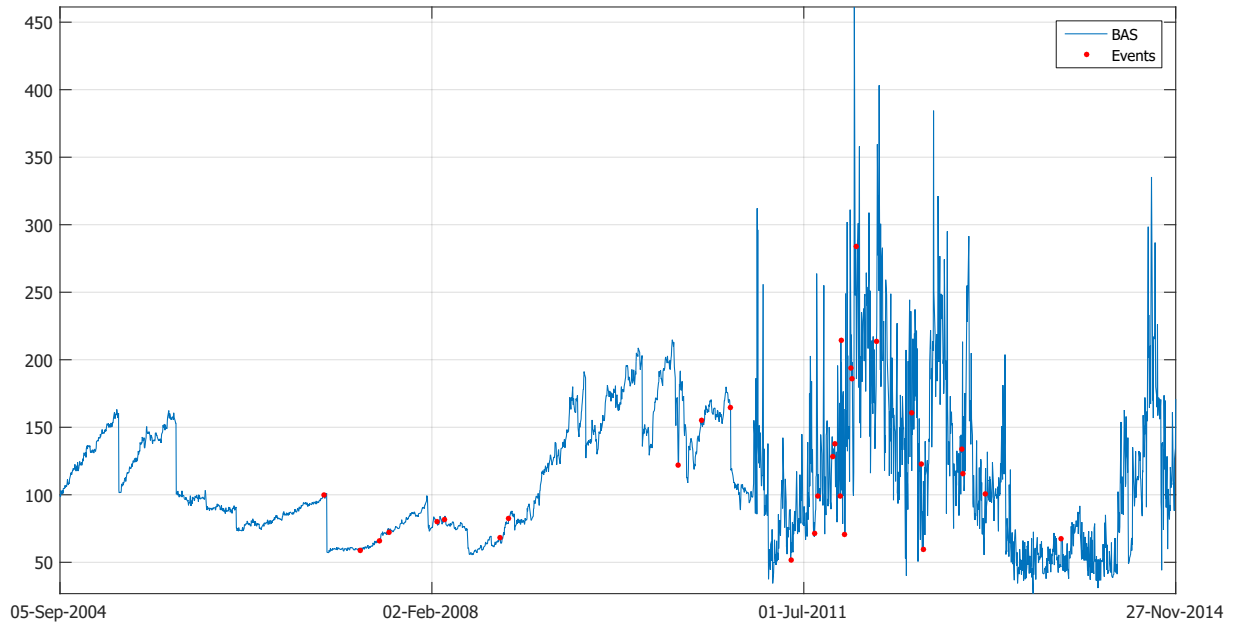
Notes: Financial variables: BAS Italy, Spread Italy, CDS Italy, FTSE MIB (main Italian Stock Price index), Vstxxx (European Implied Volatility Index), Euro Overnight Index Average (Eonia). All variables are expressed in levels for all the business days since September 2004 to November 2014. All variables but the Spread are expressed as an index=100 at the beginning of the sample. Spread is computed as the difference between German and Italian yields and expressed in basis points times 10.

Table 4.2: Daily Correlation of European BAS

	Italy	Spain	France	Germany
Italy	1	0.49***	0.56***	0.24***
Spain	0.49***	1	0.69***	0.32***
France	0.56***	0.69***	1	0.42***
Germany	0.24***	0.32***	0.42***	1

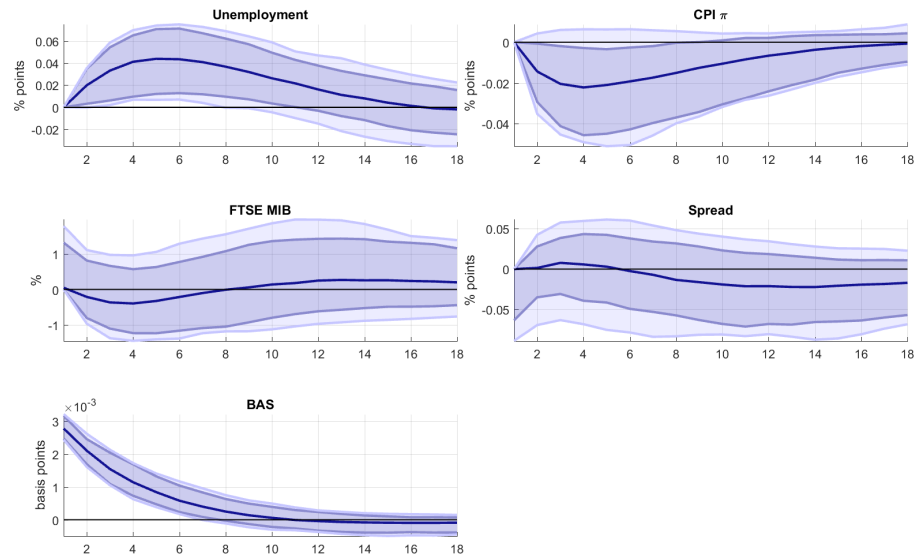
Notes: Daily correlations of 2 year sovereign BAS across countries (source: Bloomberg).

Figure 4.3: Daily BAS and Key European Events



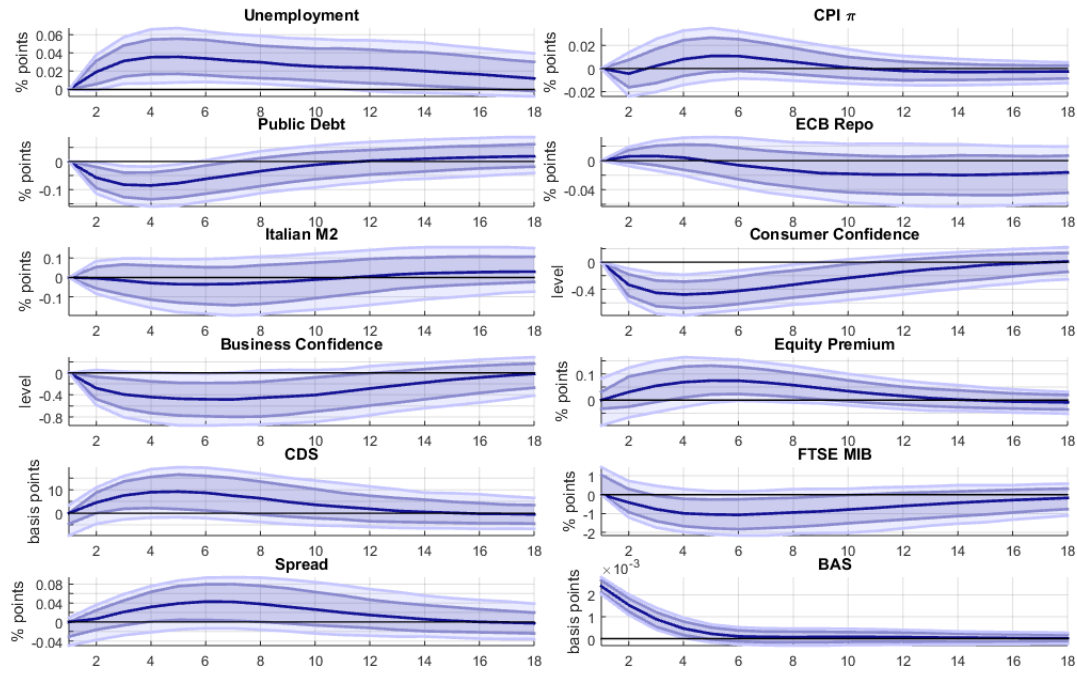
Notes: Daily BAS Italy 2 Years (blue line) and key European events (red dots). Table D.2 displays the list of all the events.

Figure 4.4: IRF to a BAS Shock in the Small System



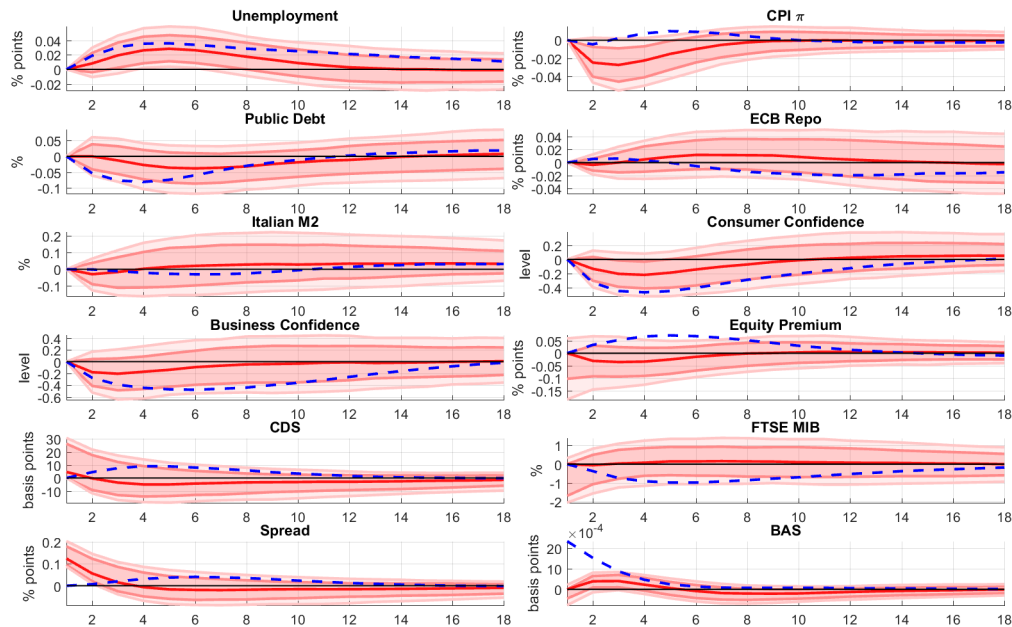
Notes: IRFs to a 1 std BAS shock (liquidity deterioration) identified through the following ordering [Unemployment, π , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure 4.5: IRF to a BAS Shock in the Large System



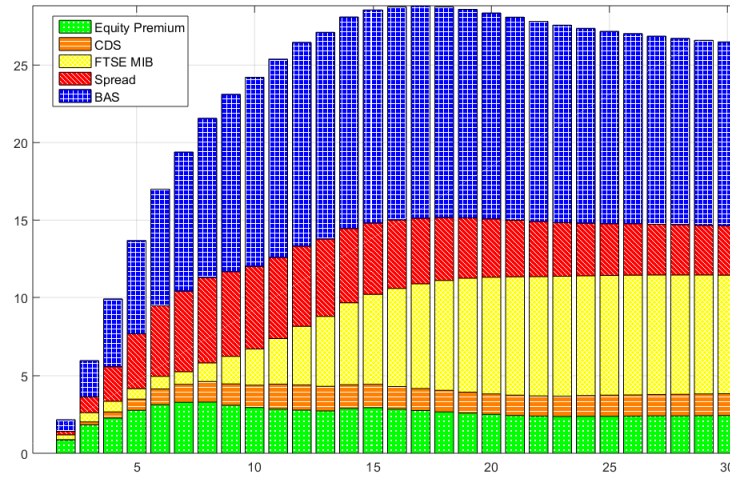
Notes: IRFs to a 1 std deviation BAS shock (liquidity deterioration) identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure 4.6: IRF to a Spread Shock



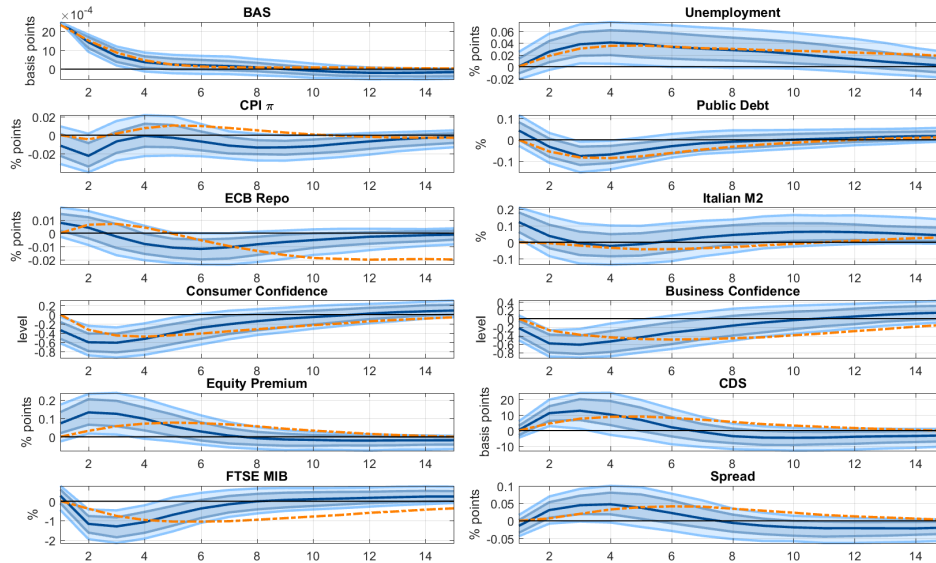
Notes: IRFs to a 1 std deviation Spread shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in red and light red, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block). Dotted line denotes the mean response to a 1 std deviation shock to BAS.

Figure 4.7: FEV of Unemployment



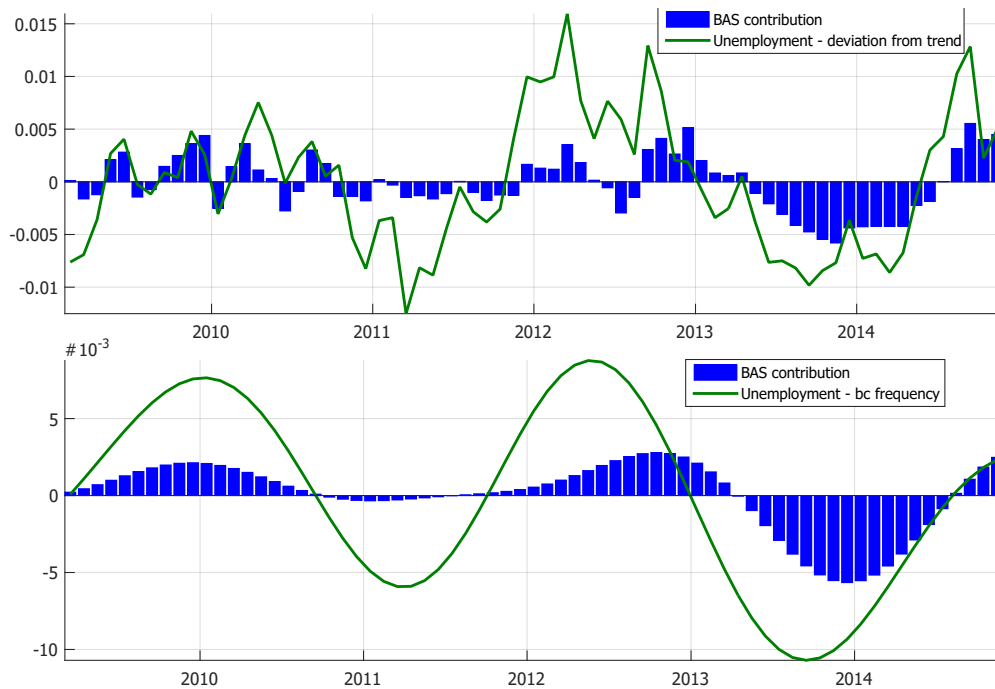
Notes: FEV of Unemployment in the VAR [Unemployment, π , Public Debt, R , M2, CC, BC, Financial Block]. The bars denote the contribution of each financial shock in explaining the volatility of Unemployment at each horizon (expressed in months).

Figure 4.8: IRF to a BAS Shock: Bridge Proxy-SVAR



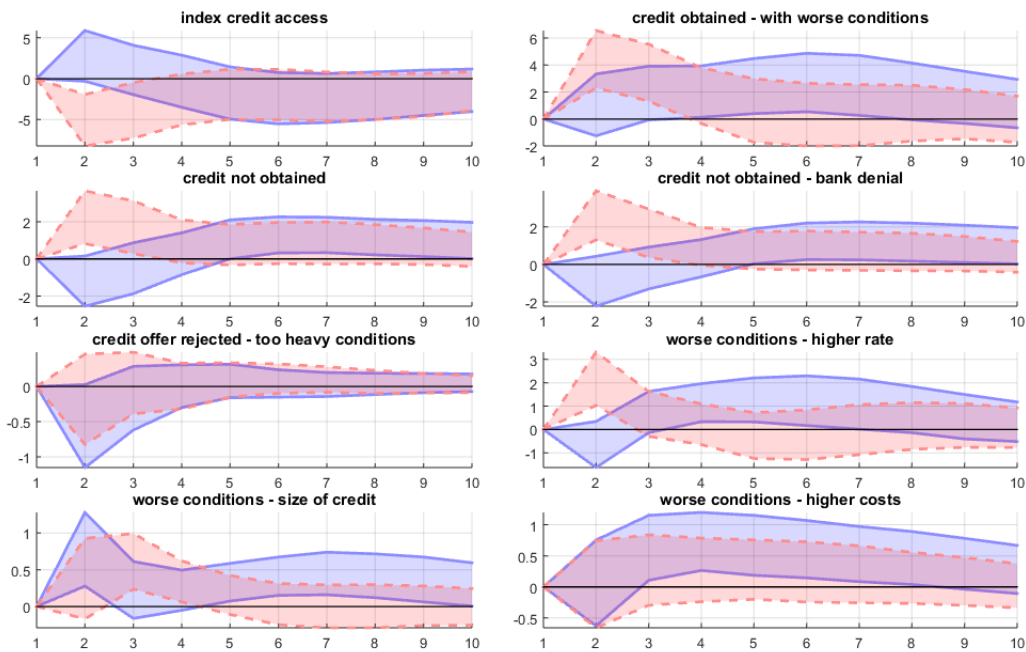
Notes: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [Unemployment, π , Public Debt, R , M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications. Dotted lines denote the mean responses of each variable to a 1 standard deviation BAS shock identified via recursive ordering.

Figure 4.9: Historical Contribution of BAS to Unemployment: Bridge Proxy-SVAR



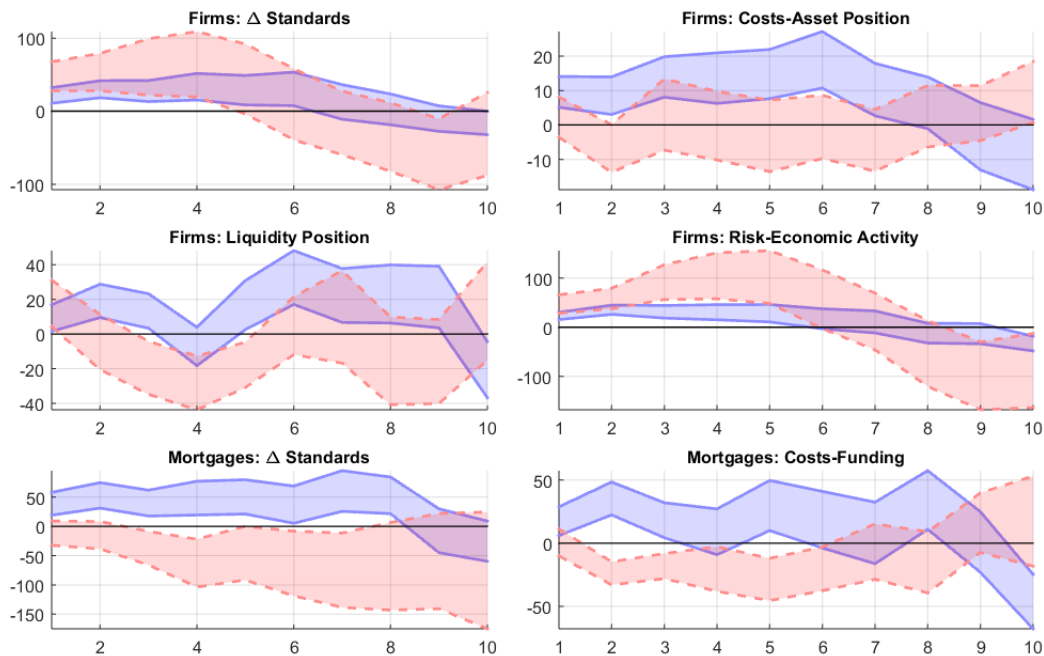
Notes: Historical contribution of BAS to Unemployment. Identified in the VAR [Unemployment, π , Public Debt, R , $M2$, CC , BC , Financial Block] through the unpredictable variation of the BAS in a daily VAR system. Upper panel - Unemployment in deviation from trend. Lower panel - Unemployment at the business cycle frequency (18 to 96 months).

Figure 4.10: Changes in Credit Market Conditions for Manufacturing Firms



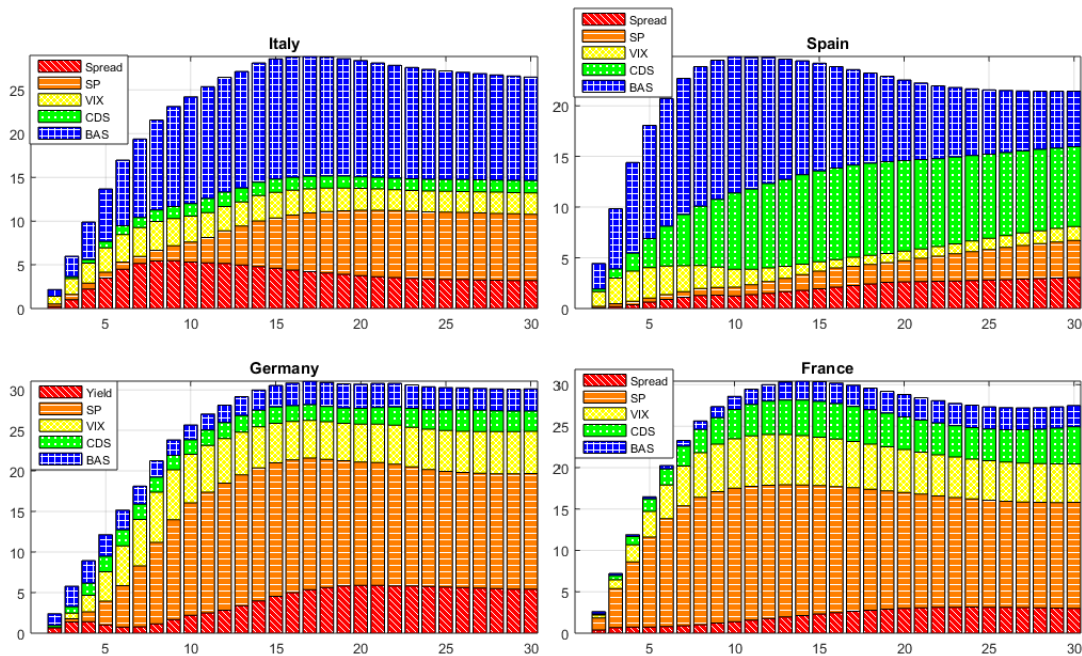
Notes: Changes in the credit market for manufacturing firms in response to a one standard positive BAS (blue) and sovereign spread (red) shocks. All figures denote change in the corresponding index reported by ISTAT. Blue and red areas denote the 68% confidence intervals computed using bootstrap and include both identification and statistical uncertainty.

Figure 4.11: Change in Banks Lending Decisions



Notes: Change in banks decisions in response to a positive shock in BAS and Spread. All the figures denote the change in the corresponding index as reported in the BLS. Blue and red areas denote the 90% confidence intervals computed using 500 bootstrap replications.

Figure 4.12: FEV of Unemployment for European Countries



Notes: FEV of Unemployment for Italy, France, Germany, and Spain. The FEVD is computed estimating a VAR for each country that includes: [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. BAS shocks are identified from all the possible rotations across the financial variables.

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Appendix A

Appendix: Chapter 1

A.1 Data

The dataset includes quarterly data for Argentina (1995Q1-2001Q3), Brazil (1996Q1-2014Q2), Chile (2003Q1-2013Q4), Mexico (1995Q1-2014Q2), Philippines (1998Q1-2006Q4), South Africa (1995Q1-2014Q2), and Turkey (1999Q1-2014Q2). The sample for Argentina ends in 2001Q3 since after its sovereign default the country interest rate was not allocative. The choice of countries and sample period is guided by macroeconomic and spread data availability. This sample is very similar to the one used by [Akinci \(2013\)](#). For the analysis, I consider emerging economies included in the J.P. Morgan Emerging Market Bond Index Global (EMBI Global).

Macroeconomic series come from IMF International Financial Statistics (IFS) database. Quarterly series of GDP and Gross Fixed Capital Formation (proxy for Investment) expressed in local currency units and current prices are deflated using the GDP deflator. Trade Balance is expressed as share of GDP at current prices and CPI is the Consumer Price Index that includes all the items. Terms of trade are computed as the ratio between export price index and import price index. All these variable are seasonally adjusted using the X13-ARIMA-SEATS before any transformation. For exchange rate, I use the Nominal Exchange Rate Index and Real Exchange Rate Index (for the case of the real shocks) computed by the Bank of International Settlements (BIS). These indexes is calculated as a geometric weighted average of bilateral exchange rates. They are available at monthly frequency and an increase indicates an appreciation. For the analysis, I use the quarterly average. Finally, the Country Interest Rate is defined as the U.S. interest rate for 10 years plus the Country Spread. For emerging economies, the spread is measured using the J.P. Morgan Emerging Markets Bond Index Global (EMBI Global). This index is computed based on: US-dollar denominated Brady bonds, Eurobonds, traded loans, and local market debt instruments

issued by sovereign and quasi-sovereign entities. The spread is computed as an arithmetic, market-capitalization-weighted average of bond spreads over U.S. Treasury bonds of similar duration. Instead of selecting countries according to a sovereign credit-rating level, as is done with the EMBI+, the EMBI Global defines emerging markets countries with a combination of World Bank-defined per capita income brackets and each country's debt-restructuring history. <http://faculty.darden.virginia.edu/liw/emf/embf.pdf> contains a detailed description of the methodology used to compute the index.

Cross Border Bank Flows denote total foreign claims (all instruments, in all currencies) outstanding to all the sectors deflated by the U.S. consumer price index. This Locational Banking dataset is compiled by the Bank of International Settlements.

All the countries are pooled for estimation. GDP, Investment, Cross Border Bank Flows, and CPI are expressed as deviations with respect to a country specific log-linear trends. Results are robust to detrending using the Hodrick-Prescott filter. Nominal Exchange Rate index (in logs), Country Interest Rate and Trade Balance/GDP are computed as deviations with respect to country-specific means.

To identify anticipated and unanticipated interest rate shocks in the U.S., I use data from the CBOT Fed Futures Market. In particular, I consider the price for each contract at the beginning of each quarter. This data is downloaded from Thomson Reuters Datastream as CBT-30 DAY FED FUNDS CONTINUOUS for different horizons ahead since January 1995. For this reason, the sample starts in January 1995. CBOT Fed Futures Market contracts trade 1 to 12 consecutive months out from a given date. Even if contracts for longer horizon are available, these are not so liquid. The contracts are always settled against the average daily effective fed funds rate for the delivery month. [http://www.jamesgoulding.com/Research_II/Fed%20Fund%20Futures/Fed%20Funds%20\(Futures%20Reference%20Guide\).pdf](http://www.jamesgoulding.com/Research_II/Fed%20Fund%20Futures/Fed%20Funds%20(Futures%20Reference%20Guide).pdf) contains detailed information about these contracts. The daily effective fed funds rate is calculated and reported by the Federal Reserve Bank of New York. I download the quarterly average of this series from St. Louis Fed. FRED database and use it as the realized value of this variable, to identify unanticipated shocks.

A.2 Identifying U.S. Interest Rate Shocks

Let's assume that the U.S. interest rate follows the following process:

$$i_t^{US} = i^{ss} + \beta \hat{y}_t + \gamma \hat{u}_t + \lambda \hat{\pi}_t + \epsilon_t$$

Then, the expectation for the interest rate one quarter ahead conditional on the information available at the beginning of quarter t is given by:

$$\mathbb{E}_{t-1} i_{t+i}^{US} = i^{ss} + \beta \mathbb{E}_{t-1} y_{t+i} + \gamma \mathbb{E}_{t-1} u_{t+i} + \lambda \mathbb{E}_{t-1} \pi_{t+i} + \mathbb{E}_{t-1} \epsilon_{t+i}$$

where the last term denotes how much markets expect the Central Bank to deviate from the systematic response. It follows that:

$$\mathbb{E}_{t-1}(i_{t+2}^{US} - i_{t+1}^{US}) = \beta \mathbb{E}_{t-1}(y_{t+2} - y_{t+1}) + \gamma \mathbb{E}_{t-1}(u_{t+2} - u_{t+1}) + \lambda \mathbb{E}_{t-1}(\pi_{t+2} - \pi_{t+1}) + \mathbb{E}_{t-1}(\epsilon_{t+2} - \epsilon_{t+1})$$

Thus, we can obtain the expected interest rate surprise as the error term of the regression (i.e. $\mathbb{E}_{t-1}(\epsilon_{t+2} - \epsilon_{t+1})$) of the anticipated change of the U.S. interest rate on the expected evolution of macroeconomic variables. An analogous expression holds for the case of $t, t+1$.

For the case of the current period:

$$\mathbb{E}_{t-1}(i_t^{US}) - i_{t-1}^{US} = \beta \mathbb{E}_{t-1}(\hat{y}_t - y_{t-1}) + \gamma \mathbb{E}_{t-1}(\hat{u}_t - u_{t-1}) + \lambda \mathbb{E}_{t-1}(\hat{\pi}_t - \pi_{t-1}) + \mathbb{E}_{t-1}(\epsilon_t - \epsilon_{t-1})$$

where all the variables dated $t-1$ are known at the period of computing the expectation. In particular, I take the first release of information for these variables that is available in SPF dataset. As usual, the expected shock is obtained as the residuals from this regression (i.e. $\mathbb{E}_{t-1}(\epsilon_t - \epsilon_{t-1})$).

Finally, for the case of unanticipated shocks:

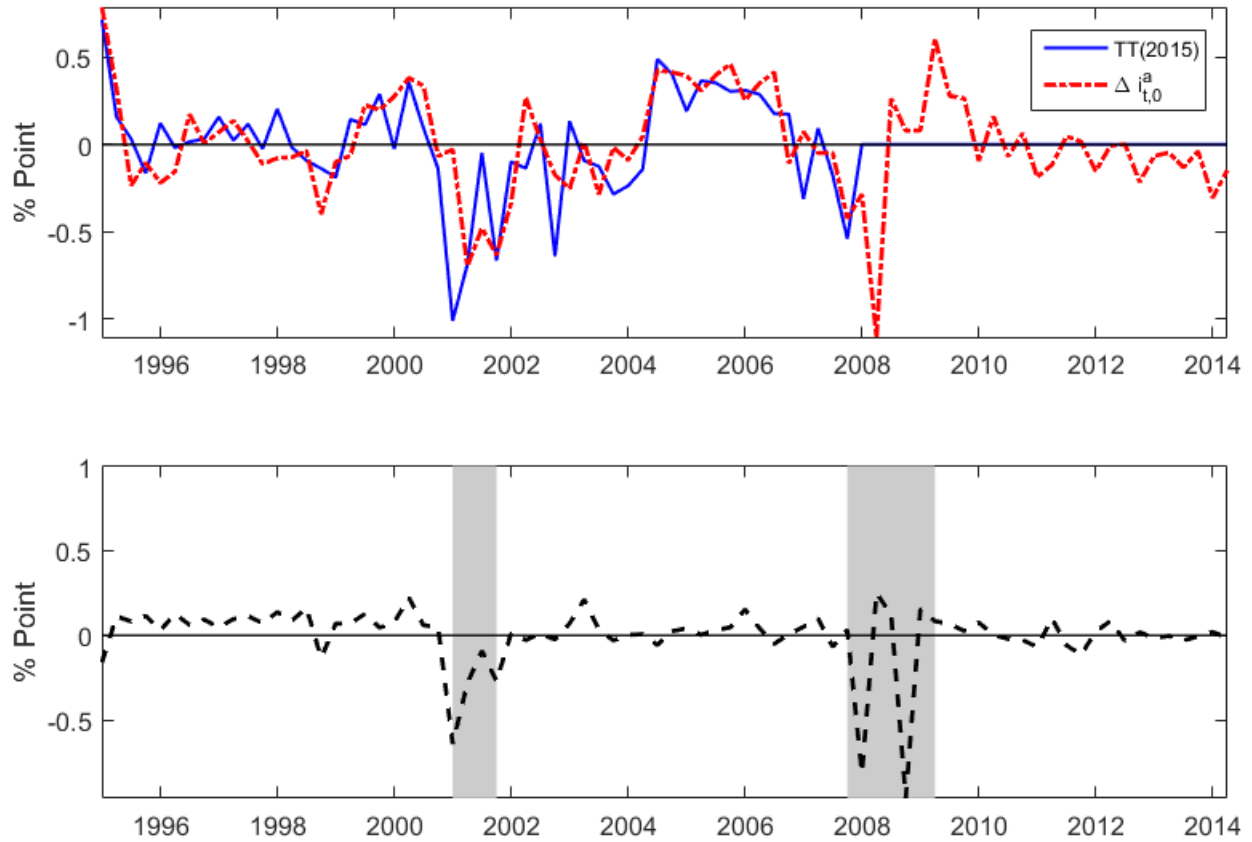
$$i_t - \mathbb{E}_{t-1} i_t = \beta (\hat{y}_t - \mathbb{E}_{t-1} \hat{y}_t) + \gamma (\hat{u}_t - \mathbb{E}_{t-1} \hat{u}_t) + \lambda (\hat{\pi}_t - \mathbb{E}_{t-1} \hat{\pi}_t) + (\epsilon_t - \mathbb{E}_{t-1} \epsilon_t)$$

The same way of obtaining the pure interest rate shocks as before (i.e. $(\epsilon_t - \mathbb{E}_{t-1} \epsilon_t)$). In all the cases, I follow [Romer and Romer \(2004\)](#) and also control for the level of the interest rate of that period to identify the pure monetary policy shock. I have also tried with Taylor rules that include persistence of the interest rate and the series are highly correlated, without affecting the results of the paper.

A.3 Series of U.S. Interest Rate Shocks

Figure A.1 displays the identified anticipated shock made at the beginning of the quarter for the current one ($\Delta i_{t,0}^a$) and the unanticipated one (Δi_t^u).

Figure A.1: Identified Anticipated and Unanticipated Shocks



Note: Top figure displays the anticipated shock computed at the beginning of the quarter for the current one ($\Delta i_{t,0}^a$) and the narrative series of monetary policy shocks (TT(2016)), updated by [Tenreiro and Thwaites \(2016\)](#). Bottom figure shows the unanticipated shock (Δi_t^u).

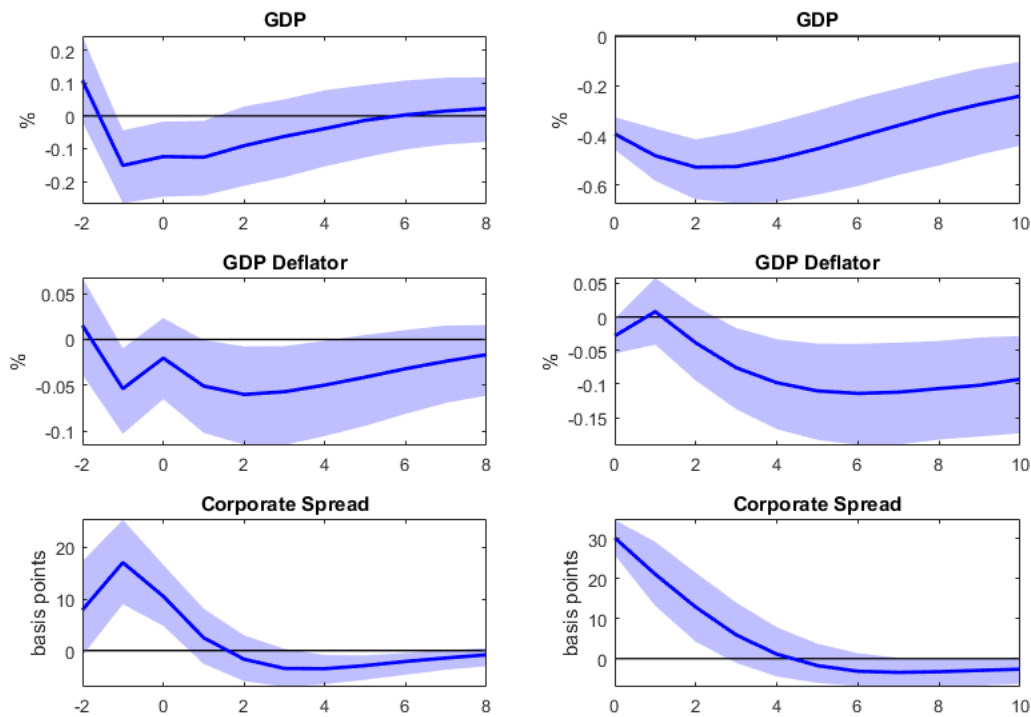
A.4 Effects of U.S. Interest Rate Shocks on U.S. Economy

In order to compare with previous monetary policy shocks and to have as a benchmark for the analysis, I estimate the effects of anticipated and unanticipated U.S. interest rate shocks on the U.S. using the empirical model proposed in Section 1.3.1. Given the short sample (1995:Q1-2014:Q2), I consider three main macroeconomic variables that summarize the

macroeconomic effects (vector X_t in expression 1.5): GDP, GDP Deflator and Corporate Spread.¹

I estimate the VAR in (log) levels without explicitly modelling the possible cointegration relations among them. In addition to a constant, I include a deterministic linear trend, where dropping it does not affect significantly the results. Following BIC criterion, I estimate a VAR with 2 lags.² Figure A.2 displays the IRFs to a two quarters anticipated (left column) and unanticipated (right column) 25 basis points contractionary U.S. interest rate shock.

Figure A.2: IRFs to an anticipated (right) and unanticipated (left) 25bp U.S. interest rate shocks



Note: IRFs to a two quarters ahead anticipated (left column) and unanticipated (right column) contractionary U.S. interest rate shock. VAR estimated in log-levels, with 2 lags and a constant and a linear trend over the period 1995:Q1-2014:Q2. Solid lines denote point estimates of impulse responses; 68% confidence bands are depicted with light-red shaded areas. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$ $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Confidence bands are computed through 1,000 bootstrap replications.

¹GDP denotes Real Gross Domestic Product, in billions of chained 2009 Dollars, seasonally adjusted (source: FRED). GDP Deflator corresponds to the Implicit Price Deflator, index 2009=100, seasonally adjusted (source: FRED). Finally, I use the Moody's Seasoned BAA Corporate Bond yield relative to yield on 10-Year Treasury constant maturity as a measure of the BAA Corporate Spread.

²Residuals are not autocorrelated with two lags. Results are robust to a four lag specification.

Both shocks induce similar qualitative effects in the U.S. economy than in small open developed economies (see Section A.5). The anticipated shock induces a contraction of GDP that starts one period before the interest rate changes. As in previous cases, this effect is coupled with an immediate increase in the Corporate Spread. Finally, the price level declines 0.05% and converges back after 5 quarters. Considering the unanticipated shock, the effect on GDP is stronger and more persistent than for the anticipated shock. Both the magnitudes and signs of the adjustment of all the variables are consistent with previous works in the literature that use different approaches to identify the monetary policy shocks. Compared to the reaction of emerging economies, the response is milder, consistent with the findings of [Mackowiak \(2007\)](#) and when the idea that “when the U.S. sneezes, emerging markets catch a cold”.

A.5 Comparison with Small Open Developed Economies

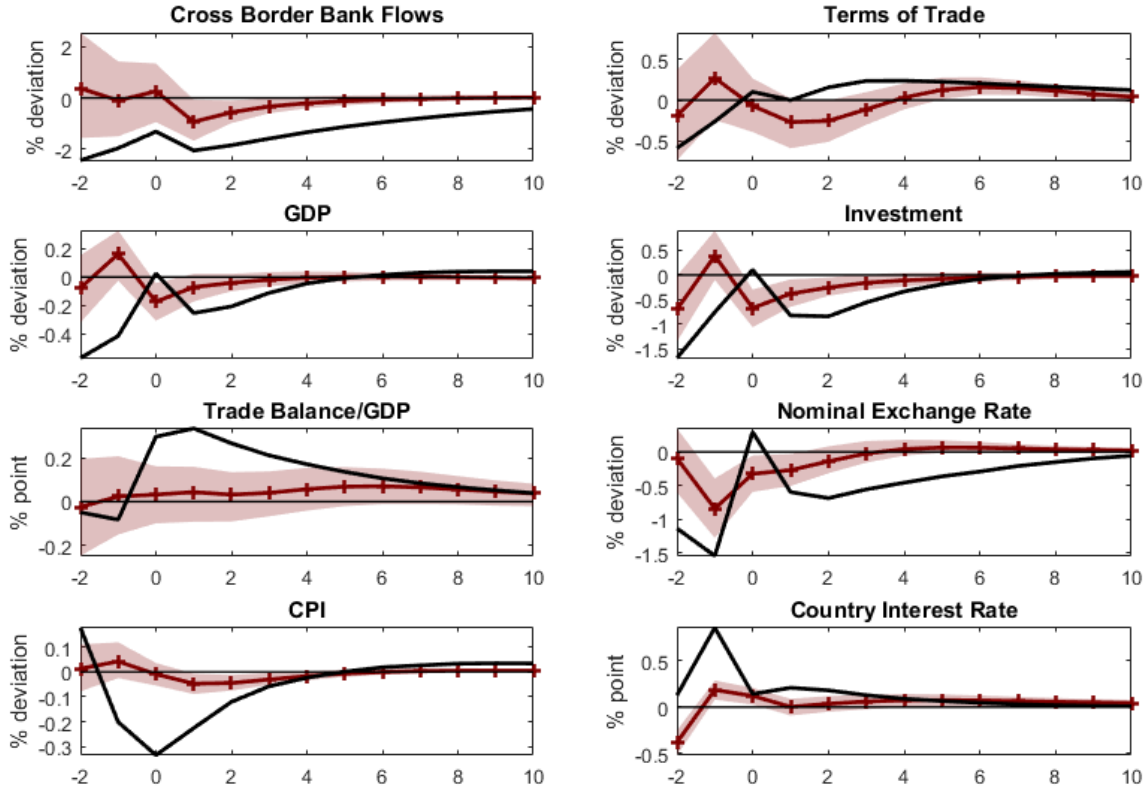
To fully understand the transmission of these shocks, I compare the responses of emerging economies to the ones of small open developed economies.³ For this reason, I estimate the same VAR presented in (1.5) with data for: Australia, Canada, Denmark, New Zealand, Norway, and Sweden for the period 1995:Q1-2014:Q2.⁴ Figure A.3 displays the IRFs to a two quarters ahead anticipated 25 basis points (one standard deviation) contractionary U.S. interest rate shock, including the point estimate of IRFs for emerging economies as a benchmark.

The response of developed economies is more delayed and less strong and persistent than for emerging ones. In particular, GDP and investment decline approximately 0.2% and 0.5% from their respective trends, only when the change in the U.S. interest rate materializes at $t = 0$. This fact can be explained by the milder responses of the cross border bank flows, country interest rate and exchange rate. Moreover, the reaction of CPI is also less significant than for emerging economies. Finally, unlike emerging economies, the trade balance does not react to this shock. This fact, together with the lack of reaction in terms of trade, shows that, for this group of countries, the shock is transmitted by the financial channel but the effects are milder compared to emerging economies. Figure A.4 displays the IRFs to an unanticipated 25 basis points contractionary U.S. interest rate shock.

³For comparison with other studies and with developed economies, in Appendix A.4 I present the IRFs of both types of shocks on the U.S. economy.

⁴Macroeconomic series come from IMF International Financial Statistics (IFS) database. The country spread for developed economies is proxied using the Citigroup World Government Bond Index for 10 year maturities. Results are robust if I compute the spread using the Long Term Interest Rate reported by the Organization for Economic Co-Operation and Development (OECD).

Figure A.3: IRFs to an anticipated 25bp contractionary U.S. interest rate shock

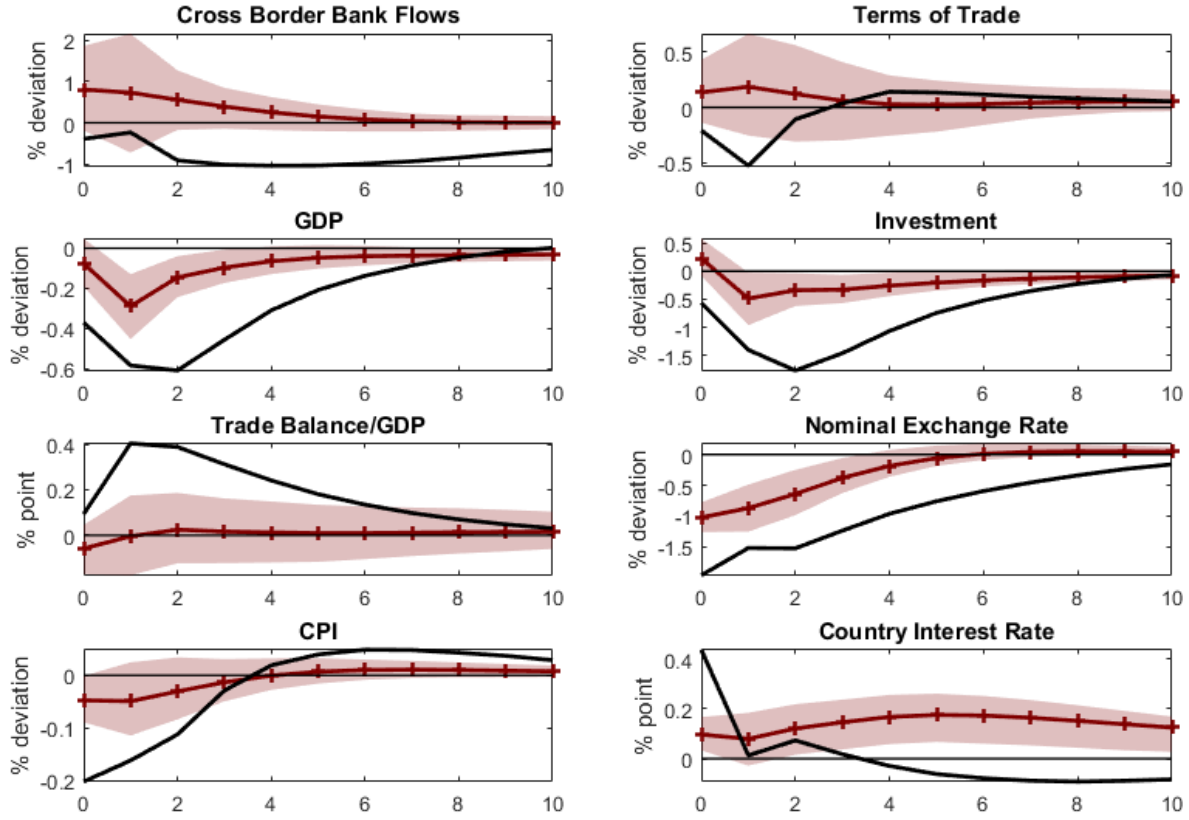


Note: Solid and plus sign lines denote the point estimate of impulse responses for emerging and developed economies, respectively. 90% confidence bands for developed economies are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. $t = 0$ denotes the period when the U.S. interest rate effectively increases. The previous two periods show the adjustment of the variables before the change in the U.S. materializes (i.e. $\Delta i_{t-2,2}^a = 1$, $\Delta i_{t-1,1}^a = 1$ and $\mathbb{E}_0 \Delta i_{t,0}^a = 1$). Confidence bands are computed through 1,000 bootstrap replications.

GDP and investment decline in response to an unanticipated contractionary shock, but their reaction is milder and less persistent than for emerging economies. These dynamics might be explained by the milder response of the country interest rate and the cross border bank flows, which remain unchanged. Moreover, the depreciation of the nominal exchange rate is also milder and less persistent than for emerging economies. Finally, like for the anticipated case, the CPI, terms of trade and trade balance do not display any significant reaction to the shock. All these responses are similar to the anticipated case.

All in all, the responses of these two groups of economies are different. One of the most important mechanisms to explain this fact is the milder reaction of financial variables (i.e cross border bank flows and country interest rate). Another significant difference is

Figure A.4: IRFs to an unanticipated 25bp contractionary U.S. interest rate shock



Note: Solid and plus sign lines denote the point estimate of impulse responses for emerging and developed economies, respectively. 90% confidence bands for developed economies are depicted with light-red shaded areas. The responses of Cross Border Bank Flows, GDP, Investment, and CPI are expressed in % deviations from their respective linear trend. The responses of Terms of Trade and Nominal Exchange Rate are expressed in % deviations. Trade Balance to GDP ratio and Country Interest Rate are expressed in annualized % points. Confidence bands are computed through 1,000 bootstrap replications.

that the trade channel is not significant for developed economies but it is significant for emerging ones. However, terms of trade do not display a significant reaction for any of the two groups.

A.6 Steady State

The following equations characterize the non-stochastic steady state of this economy. All the prices are expressed in relative terms with respect to P_t and denoted in small letters. I focus on the non-inflationary steady state (i.e. $\pi_t = \pi_t^N = 1$). In steady state, the level of external debt is:

$$d^{*H} + d^{*B} = \bar{d}^*$$

From equation 1.10:

$$\beta = \frac{1}{R^*}$$

From the definition of the trade balance (1.30):

$$tb = (R^* - 1) d^*$$

From the dynamics of bank's net worth (1.27) and the leverage constraint (1.26):

$$R = R^* + \frac{1 - \sigma^B R^* - v^B \theta^B}{\theta^B \sigma^B}$$

Using the New-Keynesian Philips Curve (1.12), the definition of the CPI based on the consumption bundle, and the labor demand of the tradable sector (1.20), we get the following non-linear system of three equations and three unknowns (p^T, p^N, w):

$$p^N = \frac{\eta}{\eta - 1} \left(\frac{1}{A^N} \right) (p^T (R^* - 1 + \delta))^\alpha w^{(1-\alpha)}$$

$$1 = \left(\chi^\mu (p^T)^{1-\mu} + (1 - \chi)^\mu (p^N)^{1-\mu} \right)^{\frac{1}{1-\mu}}$$

$$w = \frac{\left((1 - \gamma^1 - \gamma^2) A^T p^T \right)^{(\gamma^1 + \gamma^2)} \left(\frac{\gamma^2 p^T (R^* - 1 + \delta)}{\gamma^1 p^{im}} \right)^{\gamma^2 (\gamma^1 + \gamma^2)} \left(\frac{(1 + \eta^T \frac{R-1}{R}) (R^* - 1 + \delta)}{\gamma^1 A^T \left(\frac{\gamma^2 p^T (R^* - 1 + \delta)}{\gamma^1 p^{im}} \right)^{\gamma^2}} \right)^{\frac{\gamma^1 + \gamma^2}{\gamma^1 + \gamma^2 - 1}}}{1 + \eta^T \frac{R-1}{R}}$$

From the investment demand equations of tradable (1.23) and non-tradable (1.16) sectors:

$$q^T = p^T \left(1 + \eta^T \frac{R - \pi}{R} \right)$$

$$q^N = p^T$$

I can also define the shadow rent of capital to simplify some expressions:

$$u^T = q^T (R^* - 1 + \delta)$$

$$u^N = q^N (R^* - 1 + \delta)$$

From the labor demand of the non-tradable sector (1.14) and the production function of the non-tradable sector (1.11):

$$\frac{k^N}{h^N} = \left(\frac{w}{A^N p^N (1 - \alpha)} \right)^{\frac{1}{\alpha}}$$

Using the definition of u^T and the optimal demand for importable inputs (1.21):

$$im = \frac{\gamma^2 u^T k^T}{\gamma^1 p^{im} (1 + \eta^T \frac{R-1}{R})}$$

Replacing the previous expression on the production function of the tradable sector (1.17):

$$y^T = A^T \left(\frac{\gamma^2 u^T}{\gamma^1 p^{im} (1 + \eta^T \frac{R-1}{R})} \right)^{\gamma^2} (k^T)^{\gamma^1 + \gamma^2} (h^T)^{1 - \gamma^1 - \gamma^2}$$

To simplify expressions, I define $\theta^T = \left(\frac{\gamma^2 u^T}{\gamma^1 p^{im} (1 + \eta^T \frac{R-1}{R})} \right)^{\gamma^2}$. From the previous equation and the definition of u^T , I compute the capital to labor ratio in the tradable sector:

$$\frac{k^T}{h^T} = \left(\frac{q^T (R^* - 1 + \delta)}{\gamma^1 A^T p^T \theta^T} \right)^{(\gamma^1 + \gamma^2 - 1)^{-1}}$$

From the optimal demand from non-tradable (1.8) and definition of the consumption bundle (1.6):

$$\frac{c^T}{c^N} = \left(\frac{p^N \chi}{p^T (1 - \chi)} \right)^{\mu}$$

$$\frac{c}{c^T} = \left(\chi + (1 - \chi) \left(\frac{c^T}{c^N} \right)^{\frac{1}{\mu} - 1} \right)^{\left(1 - \frac{1}{\mu}\right)^{-1}}$$

From the labor supply decision (1.9):

$$h = \left(\frac{\chi \left(\frac{c}{c^T} \right)^{\frac{1}{\mu}} w (1 - b\beta)}{p^T} \right)^{\frac{1}{\omega - 1}}$$

Using the expression of $\frac{c^T}{c^N}$ together with the market clearing condition of non-tradable (1.28) and tradable goods (1.30), I get a non-linear equation to get h^N :

$$\frac{c^T}{c^N} = \frac{A^T \left(\frac{\gamma^2 u^T}{\gamma^1 p_{im} (1 + \eta^T \frac{R-1}{R})} \right) \left(\frac{k^T}{h^T} \right)^{\gamma_1 + \gamma_2} (h - h^N) - \delta \left(\frac{k^T}{h^T} \right) (h - h^N) - \delta \left(\frac{k^N}{h^N} \right) h^N - tb - p^{im} im}{A^N \left(\frac{k^N}{h^N} \right)^\alpha h^N}$$

From the optimal value of h^N and the market clearing condition of labor market (1.31), I can compute the value of h^T : $h^T = h - h^N$. Since I know the labor demand from each sector, I compute the capital stock and investment of each sector: $k^N = \left(\frac{k^N}{h^N} \right) h^N$, $k^T = \left(\frac{k^T}{h^T} \right) h^T$, $i^N = \delta k^N$ and $i^T = \delta k^T$. With these variables, using the market clearing condition (1.28) and the production function of non-tradable goods (1.11), I can compute the production of the non-tradable sector: $c^N = y^N = A^N (k^N)^\alpha (h^N)^{1-\alpha}$. Then, I recover the value of c^T and c using the following expression: $c^T = \left(\frac{c^T}{c^N} \right) c^N$ and $c = \left(\frac{c}{c^T} \right) c^T$. Using the production function of tradable goods as a function of capital and labor, I recover $y^T = A^T \left(\frac{\gamma^2 u^T}{\gamma^1 p_{im} (1 + \eta^T \frac{R-1}{R})} \right)^{\gamma^2} (k^T)^{\gamma_1 + \gamma_2} (h^T)^{1-\gamma_1-\gamma_2}$. Finally, I compute the demand for the imported input using its optimal demand condition (1.21): $im = \frac{\gamma^2 p^T y^T}{p^{im} (1 + \eta^T \frac{R-1}{R})}$.

From the working capital constraint and considering the demand for each input, I compute the demand for loans:

$$d^T = \frac{\eta^T (wh^T + p^{im} im + p^T i^T)}{R}$$

Using equation (1.32), I get $n = \frac{d^T}{\theta^B}$. From expression (1.25), I compute bank's stock of external debt $d^{*B} = \frac{n(\theta^B - 1)}{p^T}$. Finally, I compute household's stock of external debt $d^{*H} = \bar{d} - d^{*B}$ and the steady state level of terms of trade $tot = \frac{p^T}{p^{im}}$.

Appendix B

Appendix: Chapter 2

B.1 Data

We use quarterly data for the following countries and periods: Argentina 1994:Q1-2013:Q3, Brazil 1995:Q1-2014:Q3, Chile 1999:Q2-2014:Q3, Colombia 1997:Q1-2014:Q3, and Peru 1997:Q1-2014:Q3. The sample varies across countries according to data availability. For each case, we use the following series: GDP, Gross Fixed Capital Formation, Private Consumption Expenditure, and Exports and Imports of Goods and Services. All these variables are expressed in current prices and local currency units. We deflate all the variables (except the last two) using the GDP Deflator. The trade balance to GDP ratio is defined as the difference between exports and imports as a share of current GDP. All these series were downloaded from the International Financial Statistics (IFS) database, which is published by International Monetary Fund. The Real Exchange Rate index is computed by the Bank of International Settlements. This index is defined as geometric weighted averages of bilateral exchange rates adjusted by relative consumer prices. We compute the quarterly average and re-express the series such that an increase (decrease) indicates a depreciation (appreciation). All the series were seasonally adjusted using ARIMA X13. The country spread is proxied by Emerging Markets Bond Index (EMBI) Global (Stripped Spread) computed by JP Morgan, which is a composite of different US dollar-denominated bonds. The Stripped Spread is computed as an arithmetic, market-capitalization-weighted average of bond spreads over US Treasury bonds of comparable duration. Finally, for the international variables, we use the Moody's Seasoned Baa Corporate Bond minus the Federal Funds Rate, available online at FRED under the name BAAFFM, as a proxy for the corporate spread and we compute the Commodity Terms of Trade index for each country following the procedure of [Shousha \(2016\)](#). In particular, we use the IMF Primary Commodity Price data set and the country-specific weights in Table B.1, as calculated by

[Shousha \(2016\)](#) using annual trade data from UN Comtrade from 1994-2013. The country specific commodity price index is expressed in real terms by dividing it by the U.S. import price of manufactured goods from industrialized countries (source: FRED, code: INDUSMANU).

Table B.1: Main exported commodities by country-CTOT weights

Country	Main commodities
Argentina	Soybeans (41%), Crude Oil (12%), Maize (8.9%)
Brazil	Soybeans (22%), Iron Ore (17%), Sugar (9%)
Chile	Copper (72%), Fish (9%), Wood (7%)
Colombia	Crude Oil (45%), Coal (19%), Coffee (18%)
Peru	Copper (34%), Gold (29%), Zinc (11%)

Source: [Shousha \(2016\)](#)

For the robustness exercises, we use the Export and Import Price index to compute the TOT series for each country. These indexes were downloaded from the national central banks (Brazil, Chile, Colombia, and Peru) and IMF (Argentina). The country-specific commodity price future index was computed using the average price of the commodity future contracts of the main commodities exported by each country. We employ the same weights as for the commodity based price index, choosing for each good the longest maturity available. In particular, we employ the following contracts: Coffee (6th continuous contract), Cooper, Corn (6th continuous contract), Gold (7th continuous contract), Maize (6h continuous contract), Oil (12th continuous contract), Soybean (8th continuous contract), and Sugar (4th continuous contract). For some commodities (Coal, Fish, Iron Ore, Wood, and Zinc), quotations from future markets are not available for the whole sample. In these cases, we do not consider the good in case it is not representative or we replace it for another relevant commodity exported by the same country. The data for commodity prices was downloaded from Quandl.¹ As a proxy for government expenditure, we use the Government Consumption Expenditure from the IFS database. We deflate this variable using the GDP Deflator. For the robustness exercises, we also use the stock price index for each country. In particular, we use the Merval (Argentina), Bovespa (Brazil), IPGA (Chile), COLCAP (Colombia), and IGBVL (Peru). The historical series were downloaded from Datastream. Finally, the U.S. interest rates are downloaded from the FRED.

¹<https://www.quandl.com> provides continuous series for many commodities based on data from CME.

The Real TBill rate is computed as the quarterly average of the nominal 3 month TBill rate (annualized) minus the U.S. CPI inflation rate over the previous twelve months.

For the annual specification, we use the same sample of poor and emerging countries and periods as [Schmitt-Grohe and Uribe \(2017\)](#). In particular, the panel contains data for the period 1980 to 2011 for the following countries: Algeria, Argentina, Bolivia, Botswana, Brazil, Burundi, Cameroon, Central African Republic, Colombia, Congo Dem. Rep., Costa Rica, Cote d'Ivoire, Dominican Republic, Egypt Arab Rep., El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Korea Rep., Madagascar, Malaysia, Mauritius, Mexico, Morocco, Pakistan, Paraguay, Peru, Philippines, Senegal, South Africa, Sudan, Thailand, Turkey, and Uruguay. The sample used for the specification "SGU (Our Sample) - Annual" includes the following countries: Argentina, Brazil, Colombia, Peru. All the data comes from the World Development Indicators (WDI) database, which is published by the World Bank, and is available online at the authors' websites.

Appendix C

Appendix: Chapter 3

C.1 Conservative Identification - Orthogonalization

Our contribution concerns the way of studying the relationship between HF and LF variables, independently of the particular identification scheme chosen. Nonetheless, we can take an additional step if we restrict the class of DGPs to the subset in which each structural shock is associated with one variable.¹ Using the representation in eq. (3.3), this assumption means that $B_{11} > B_{21}$; $B_{22} > B_{12}$.² Then, consider a case in which the HF identification employs a VAR, and the researcher does not dispose of other, economic based, identification schemes (first best). In this setting, we can think of a recursive ordering where y is placed last, after all the variables that constitute the information set Ψ , as a second best identification. Such procedure is namely an orthogonalization and it is equivalent to use the residuals from the regression of the variable of interest y on its previous lags p (where p are the lags included in the HF-VAR) and on the contemporaneous values and lags of Ψ :

$$y_t = \sum_{l=1}^p \beta^l y_{t-l} + \sum_{l=0}^p \alpha^l \Psi_{t-l} + e_t \quad e_t \sim WN \quad (C.1)$$

If each shock is associated with a variable, regressing the variable of interest y_t on Ψ_t yields the new information introduced in the system uniquely by y_t , that we label ε_t^y .

Intuitively, the econometrician is likely to face identification trade-offs across different schemes in applied research. The researcher observes the high frequency reduced form

¹This means that each innovation enter the system mainly through a specific variable. For example, we call structural shock an innovation in the variable y which is orthogonal to the innovations in other variables. Notice that this is one of the many interpretations of innovation.

²The assumption is implicit in our notation ε_t^y and ε_t^x , but Section 3.2.2 is actually more general.

residual \dot{u}_t^y which is a linear combination of the structural shocks:

$$\begin{aligned}\dot{u}_t^y &= b_{22}\varepsilon_t^y + b_{21}\varepsilon_t^x \\ &= b_{22}(\mu_1\varsigma_t + \mu_2\phi_t) + b_{21}\varepsilon_t^x\end{aligned}\tag{C.2}$$

Suppose that ς_t satisfies the strength requirement of an *IV*, such that the resulting estimates are statistically reliable: $\mathbb{E}[\varsigma_t u_\tau^y] = \mu_1 \neq 0$. Given this condition, the econometrician should favor the most conservative HF identifications that, even washing out the component ϕ_t , does not capture in the proxy any other shocks ε_t^x . While the former issue does not yield distorted estimates, this latter event would induce biases by violating the exclusion restriction.

Furthermore, we wish to highlight two advantages of this conservative identification. First, the orthogonalization is robust to misspecifications thanks to the instrumental variable approach embedded into it. The IV approach allows us to employ only an exogenous variation (a component of the true structural shock) and not the whole structural shocks. Second, this identification yields identified shocks orthogonal with respect to the remainder of the current and past information set. Macroeconomic variables are explicitly unobservable at LF and cannot be included in the HF system. However, financial variables respond to the new available information on macroeconomic variables in real-time.

C.1.1 An Illustrative Example

Let us consider how the conservative identification performs with respect to a more relaxed identification. We study a simply bivariate system and compare violations in the exclusion restriction in our instrument $\hat{\varepsilon}_t^y$, i.e. how large is the component of ε_t^x captured in $\hat{\varepsilon}_t^y$. The system is structured as

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix}\tag{C.3}$$

where we normalized $b_{11} = b_{22} = 1$. Recall the assumption $b_{11} > b_{12}$ and $b_{22} > b_{21}$ such that there is a mapping between variables and shocks. We restrict the parameter space to positive values of b_{12} and b_{21} to simplify the analysis. Moreover, we are only interested in studying the impact matrix B , so we consider a process without persistence:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix}\tag{C.4}$$

Under the relaxed identification scheme, we simply take the reduced form residual of y as structural shock. The component of ε_t^x captured in this measure is b_{21} , i.e. how much ε_t^x impacts on y_t :

$$\hat{\varepsilon}_t^{yR} = b_{21}\varepsilon_t^x + \varepsilon_t^y \quad (\text{C.5})$$

Under the conservative identification scheme, we regress y_t on x_t and take the residuals:

$$\begin{aligned} y_t &= \theta x_t + \epsilon_t & \epsilon_t &\sim WN \\ b_{21}\varepsilon_t^x + \varepsilon_t^y &= \theta (\varepsilon_t^x + b_{12}\varepsilon_t^y) + \epsilon_t & \epsilon_t &\sim WN \end{aligned} \quad (\text{C.6})$$

Applying the definition of OLS we obtain:

$$\begin{aligned} \hat{\theta}_{OLS} &= \mathbb{E}[x_t x_t]^{-1} \mathbb{E}[x_t y_t] \\ &= \frac{\mathbb{E}[(b_{21}\varepsilon_t^x + \varepsilon_t^y)(\varepsilon_t^x + b_{12}\varepsilon_t^y)]}{\mathbb{E}[(\varepsilon_t^x + b_{12}\varepsilon_t^y)(\varepsilon_t^x + b_{12}\varepsilon_t^y)]} \\ &= \frac{b_{21} + b_{12}}{1 + b_{12}^2} \end{aligned} \quad (\text{C.7})$$

The residuals are computed as

$$\begin{aligned} y_t - x_t \hat{\theta}_{OLS} &= b_{21}\varepsilon_t^x + \varepsilon_t^y - \hat{\theta}_{OLS}(\varepsilon_t^x + b_{12}\varepsilon_t^y) \\ &= (1 - b_{12}\hat{\theta}_{OLS})\varepsilon_t^y + (b_{21} - \hat{\theta}_{OLS})\varepsilon_t^x \\ &= \left(1 - \frac{b_{12}^2 + b_{21}b_{12}}{1 + b_{12}^2}\right)\varepsilon_t^y + \left(b_{21} - \frac{b_{12} + b_{21}}{1 + b_{12}^2}\right)\varepsilon_t^x \\ \hat{\varepsilon}_t^{yC} &= \Lambda \varepsilon_t^y + \Gamma \varepsilon_t^x \end{aligned} \quad (\text{C.8})$$

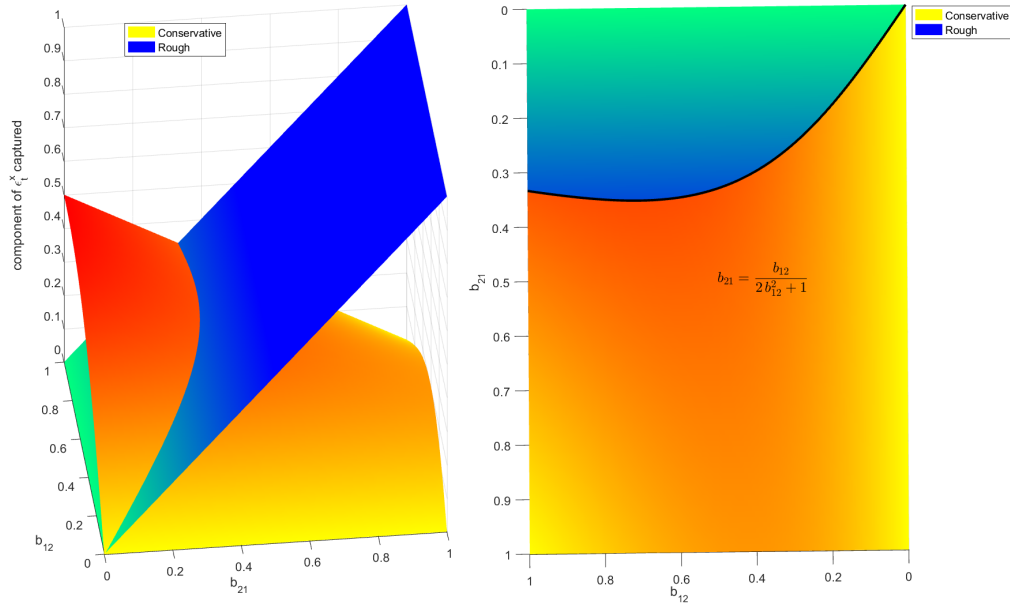
Γ represents a measure of violation in the exclusion restriction. In two extreme cases: $b_{21} = 0 \Rightarrow \|\Gamma\| = \frac{b_{12}}{1+b_{12}^2}$ and $b_{12} = 0 \Rightarrow \|\Gamma\| = 0$. The comparison between relaxed and conservative identification reduces to the comparison between Γ and b_{21} . The condition $\Gamma < b_{21}$ is satisfied $\forall \{b_{12}, b_{12}\}$ as ε_t^x enters negatively in $\hat{\varepsilon}_t^{yC}$. This is likely to downward bias $\hat{\varepsilon}_t^{yC}$ and make the first stage in the *Bridge* ineffective. However, let us consider the modulus of Γ for completeness:

$$\begin{aligned} \|\Gamma\| &< b_{21} \Rightarrow -b_{21} < \Gamma < b_{21} \\ b_{21} &> \frac{b_{12}}{(2b_{12}^2 + 1)} \end{aligned} \quad (\text{C.9})$$

A graphical representation of the analytical results is provided below in Fig. C.1. The same results hold in a simulation design (Fig. C.2). The conservative identification is overall better in building an exogenous instrument than a more relaxed identification. The exception

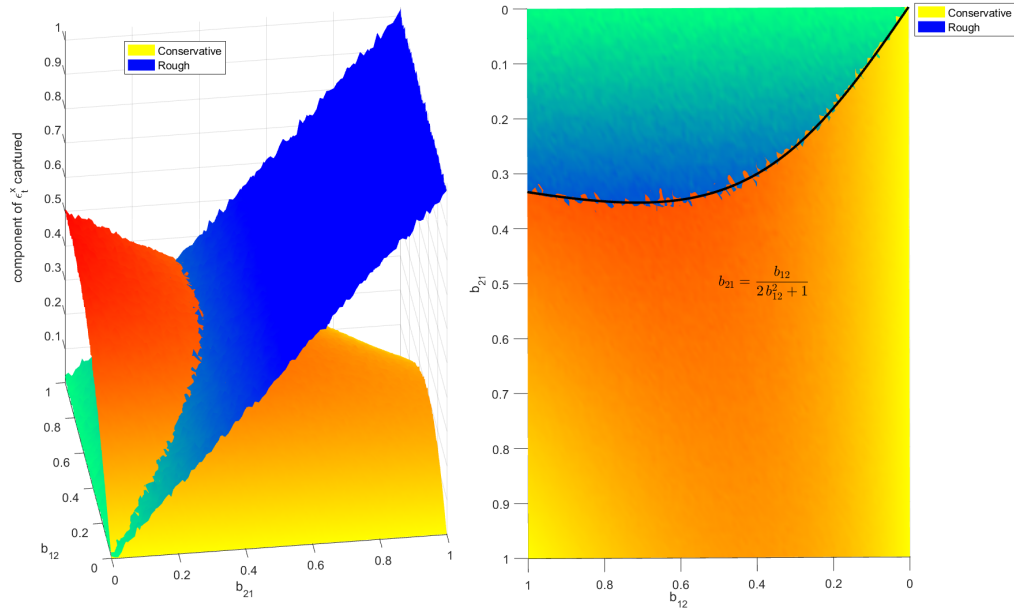
comes from low values of b_{21} . However, when b_{21} overcomes a certain threshold than the gains from the conservative over the relaxed identification are exponentially increasing (and the value of b_{12} does not matter anymore). In terms of economic interpretation, the *Bridge* is designed to study the effect of a shock to an HF variable y . b_{21} represents how much y responds to other shocks on impact. We can realistically state that, if y is financial variable, b_{21} takes large values and, in such a way, the conservative identification dominates the relaxed identification.

Figure C.1: Violation of the exclusion restriction - analytical case



Notes: Comparison of the violation of the exclusion restrictions between our conservative and rough (relax) identifications over the parameter space $\{b_{12}, b_{21}\} = \{0, 1\} \times \{0, 1\}$. The left panel is a 3D plot, while in the right panel the size of the violation of the exclusion restriction have been collapsed. Where colors are cold $b_{21} < \Gamma$, where they are warm $b_{21} > \Gamma$. In black we report the analytical condition where b_{21} crosses Γ .

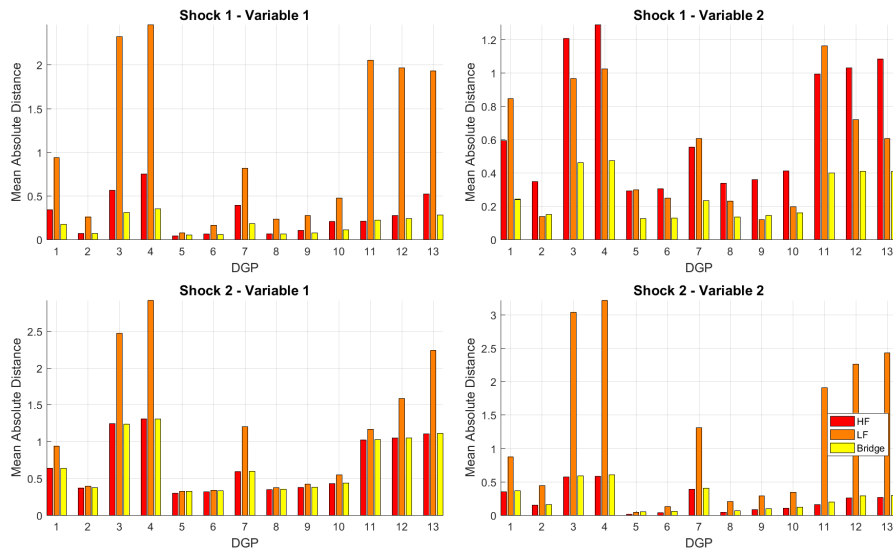
Figure C.2: Violation of exclusion restriction - simulation



Notes: Comparison of the violation of the exclusion restrictions between our conservative and rough (relax) identifications over the parameter space $\{b_{12}, b_{21}\} = \{0, 1\} \times \{0, 1\}$. The left panel is a 3D plot, while in the right panel the size of the violation of the exclusion restriction have been collapsed. Where colors are cold $b_{21} < \Gamma$, where they are warm $b_{21} > \Gamma$. In black we report the analytical condition where b_{21} crosses Γ .

C.1.2 Monte Carlo Performances

Figure C.3: MAD comparison in the two variable system: misspecification



Notes: Mean Absolute Distance (MAD) of IRFs estimated with the HF-VAR, LF-VAR and Bridge Proxy-SVAR in the 13 DGP cases. Time aggregation follows a skip-sampling scheme. Our conservative identification at HF is applied in this case. IRFs are standardized with respect to the true size of the shock.

Table C.1: Performance comparison in Monte Carlo simulations - additional cases

MAD GAINS OVER LF-VAR		
Identification	Temporal Aggregation Scheme	
	SKIP-SAMPLING	AVERAGING
<u>Full information at HF for Bridge: Quarterly-Monthly Frequency Mismatch</u>		
HF-VAR	21.2%	41.4%
Bridge	20%	36.7%
Bridge - conservative identification	21.7%	38.3%
<u>Full information at HF for Bridge: Monthly-Daily Frequency Mismatch</u>		
HF-VAR	70%	81.2%
Bridge	65.6%	72.6%
Bridge - conservative identification	65.2%	74.7%

Notes: Performance comparison across the counter-factual HF-VAR, the LF-VAR and the Bridge Proxy-SVAR. Performances are evaluated in terms of the Mean Absolute Distance (MAD) between the true IRFs and the estimated IRFs in 100 randomly parametrized DGPs. One summary statistic is computed based all the combinations of shocks-variables in the system. The gains are expressed as percentage MAD gains over the LF-VAR. We analyze different cases for a VAR(1) DGP: I) The Bridge employs full information at HF and the impact matrix B is diagonally dominated; II) The Bridge employs full information at HF and no restrictions are imposed on the impact matrix B; III) The Bridge employs only partial information at HF and no restrictions are imposed on the impact matrix B. The system features nine variables and the frequency mismatch is three (quarterly-monthly case). When possible, i.e. under full information, for the Bridge, we report both the results under the same identification of LF/HF-VAR and our conservative identification.

C.2 Skip Sampling Temporal Aggregation

C.2.1 Temporal Aggregation Bias

Following the recursive structure embodied in the impact matrix B , a Cholesky decomposition on the reduced form residuals at HF would yield the impact matrix itself:

$$Chol(BB') = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} = B \quad (C.10)$$

However, when we move to the time aggregation case, even the correct identification scheme yields biases. In fact, we impose the zero restriction on the time aggregated reduced form residuals, whose variance-covariance matrix is given by:

$$\begin{aligned} \Omega &= BB' + ABB'A' \\ &= \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{bmatrix} \end{aligned} \quad (C.11)$$

$$\begin{aligned}
\omega_{11} &= a_{12} [a_{12}b_{22}^2 + b_{21} (a_{11}b_{11} + a_{12}b_{21})] + b_{11}^2 + a_{11}b_{11} (a_{11}b_{11} + a_{12}b_{21}) \\
\omega_{12} &= a_{22} [a_{12}b_{22}^2 + b_{21} (a_{11}b_{11} + a_{12}b_{21})] + b_{11}b_{21} + a_{21}b_{11} (a_{11}b_{11} + a_{12}b_{21}) \\
\omega_{21} &= a_{12} [a_{22}b_{22}^2 + b_{21} (a_{21}b_{11} + a_{22}b_{21})] + b_{11}b_{21} + a_{11}b_{11} (a_{21}b_{11} + a_{22}b_{21}) \\
\omega_{22} &= a_{22} [a_{22}b_{22}^2 + b_{21} (a_{21}b_{11} + a_{22}b_{21})] + b_{21}^2 + b_{22}^2 + a_{21}b_{11} (a_{21}b_{11} + a_{22}b_{21})
\end{aligned}$$

The Cholesky decomposition of Ω yields:

$$Chol(\Omega) = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \quad (C.12)$$

$$\begin{aligned}
c_{11} &= (a_{11}^2b_{11}^2 + 2a_{11}a_{12}b_{11}b_{21} + a_{12}^2b_{21}^2 + a_{12}^2b_{22}^2 + b_{11}^2)^{\frac{1}{2}} \\
c_{21} &= \left(\frac{b_{11}b_{21} + a_{11}a_{21}b_{11}^2 + a_{12}a_{22} * b_{21}^2 + a_{12}a_{22}b_{22}^2 + a_{11}a_{22}b_{11}b_{21} + a_{12}a_{21}b_{11}b_{21}}{a_{11}^2b_{11}^2 + 2a_{11}a_{12}b_{11}b_{21} + a_{12}^2b_{21}^2 + a_{12}^2b_{22}^2 + b_{11}^2} \right)^{\frac{1}{2}} \\
c_{22} &= \left[(b_{21}^2 + b_{22}^2 + a_{21}^2b_{11}^2 + a_{22}^2b_{21}^2 + a_{22}^2b_{22}^2 + 2a_{21}a_{22}b_{11}b_{21}) * \right. \\
&\quad (a_{11}^2b_{11}^2 + 2a_{11}a_{12}b_{11}b_{21} + a_{12}^2b_{21}^2 + a_{12}^2b_{22}^2 + b_{11}^2) + \\
&\quad \left. - (b_{11}b_{21} + a_{11}a_{21}b_{11}^2 + a_{12}a_{22}b_{21}^2 + a_{12}a_{22}b_{22}^2 + a_{11}a_{22}b_{11}b_{21} + a_{12}a_{21}b_{11}b_{21})^2 \right]^{\frac{1}{2}} * \\
&\quad (a_{11}^2b_{11}^2 + 2a_{11}a_{12}b_{11}b_{21} + a_{12}^2b_{21}^2 + a_{12}^2b_{22}^2 + b_{11}^2)^{-1/2}
\end{aligned}$$

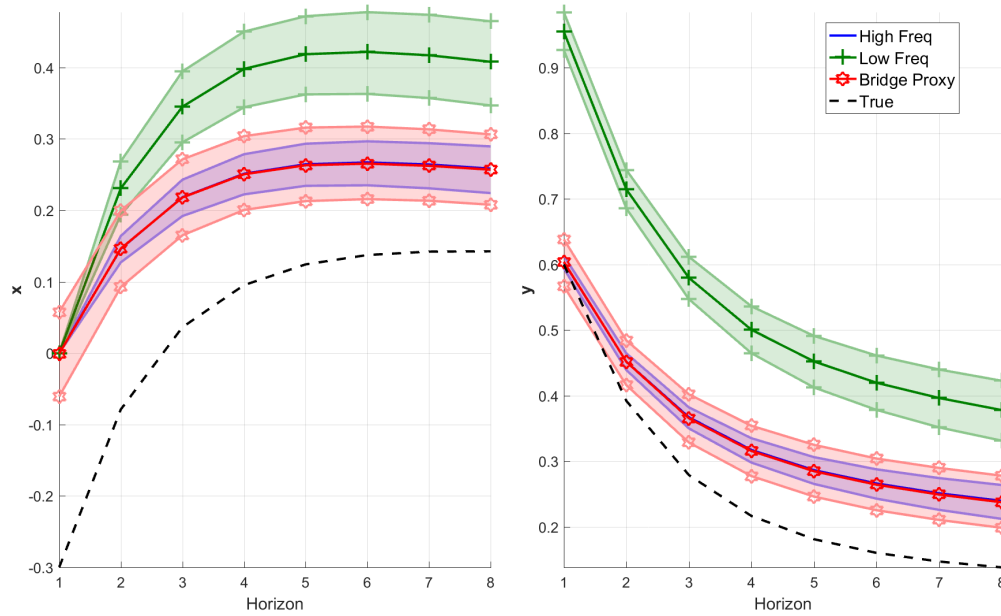
where $\{c_{11}, c_{12}, c_{22}\} \neq \{b_{11}, b_{12}, b_{22}\}$ and the bias depends on the parametrization of of the DGP.

C.2.2 Monte Carlo - Additional Content

The parametrizations of the DGP (eq. 3.28) that we employ in the bivariate Monte Carlo simulations are:

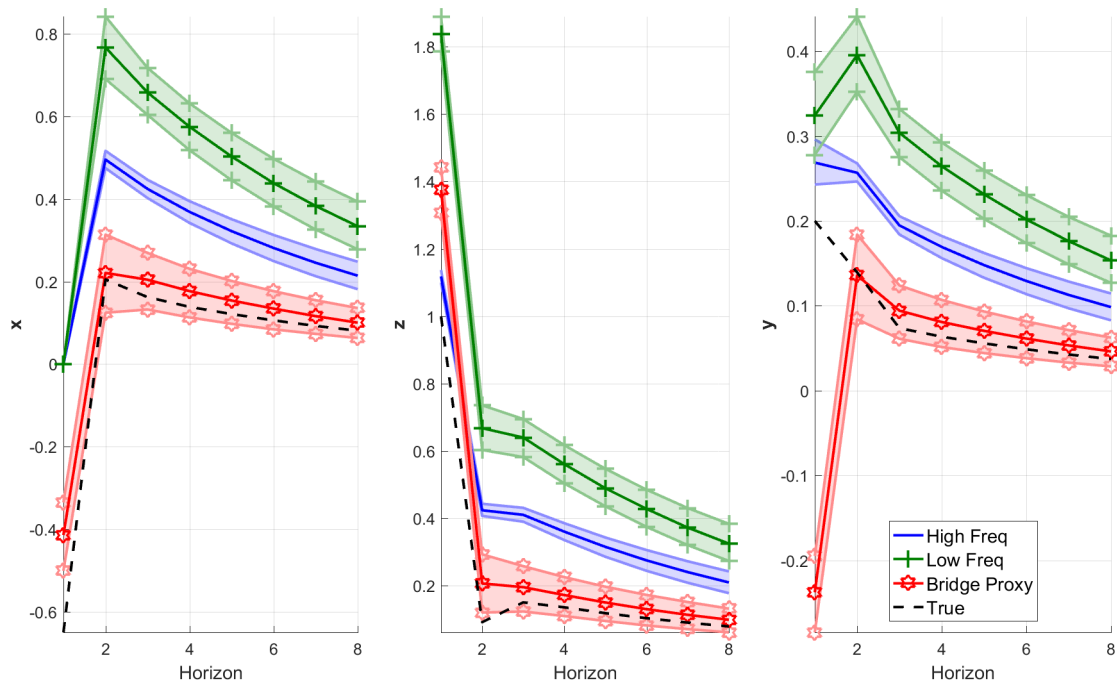
$$\begin{aligned}
\{\rho, \rho_l, \rho\} &= \{0.5, 0.4, , 0.4\}; \{0.5, 0.08, , 0.4\}; \{0.9, 0.08, , 0.08\}; \{0.9, 0.1, , 0.08\}; \\
&\{0.1, 0.1, , 0.1\}; \{0.1, 0.4, , 0.4\}; \{0.1, 0.08, , 0.08\}; \{0.5, 0.1, , 0.1\}; \\
&\{0.5, 0.2, , 0.2\}; \{0.5, 0.4, , 0.2\}; \{0.9, 0.01, , 0.01\}; \{0.9, 0.04, , 0.04\}; \\
&\{0.9, 0.08, , 0.04\};
\end{aligned}$$

Figure C.4: IRFs2 in the two variable system: misspecification



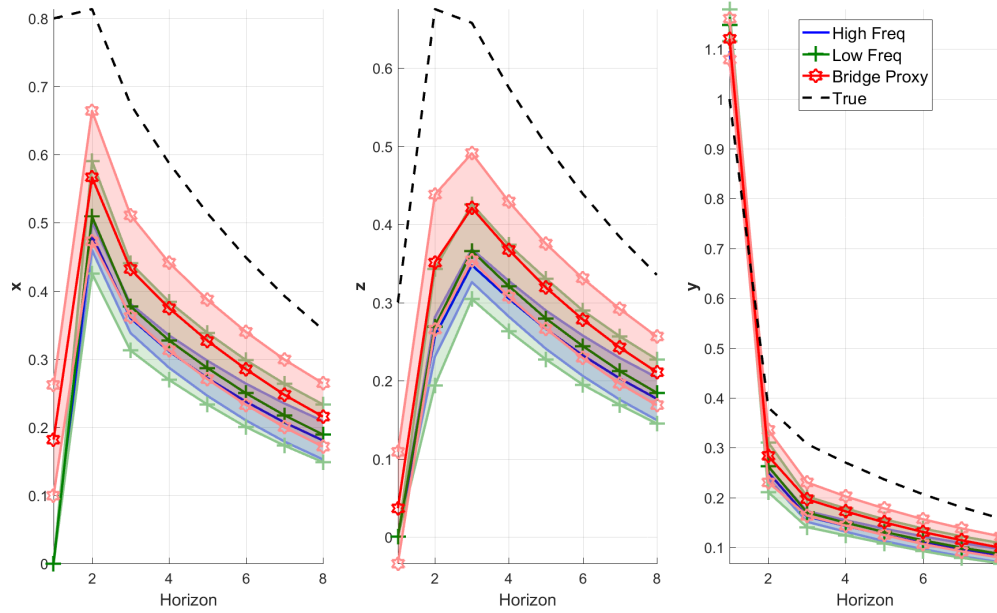
Notes: IRFs to a shock in the second variable (y) in the bivariate system. The true IRF is represented by the dotted black line. The shock is identified through a wrong recursive structure in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands across 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.5: IRF2 in the practical case



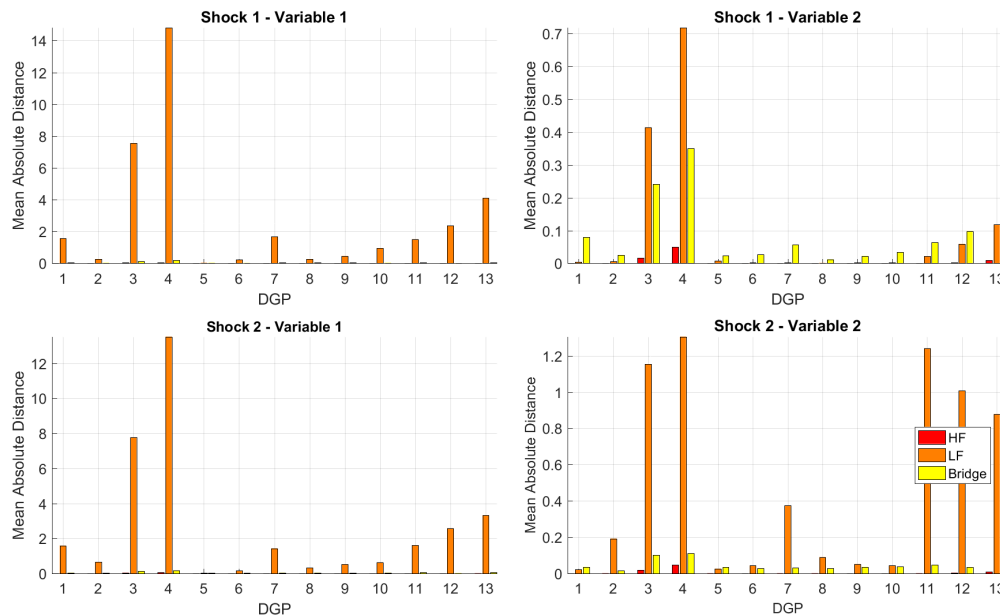
Notes: IRFs to a shock in the second variable (z) in the three variable system. Left panel - first variable (x); middle panel - second variable (z); right panel - third variable (y). The shock is identified through a wrong Cholesky in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands. The black line is the true IRF. Time aggregation follows a skip-sampling scheme.

Figure C.6: IRF3 in the practical case



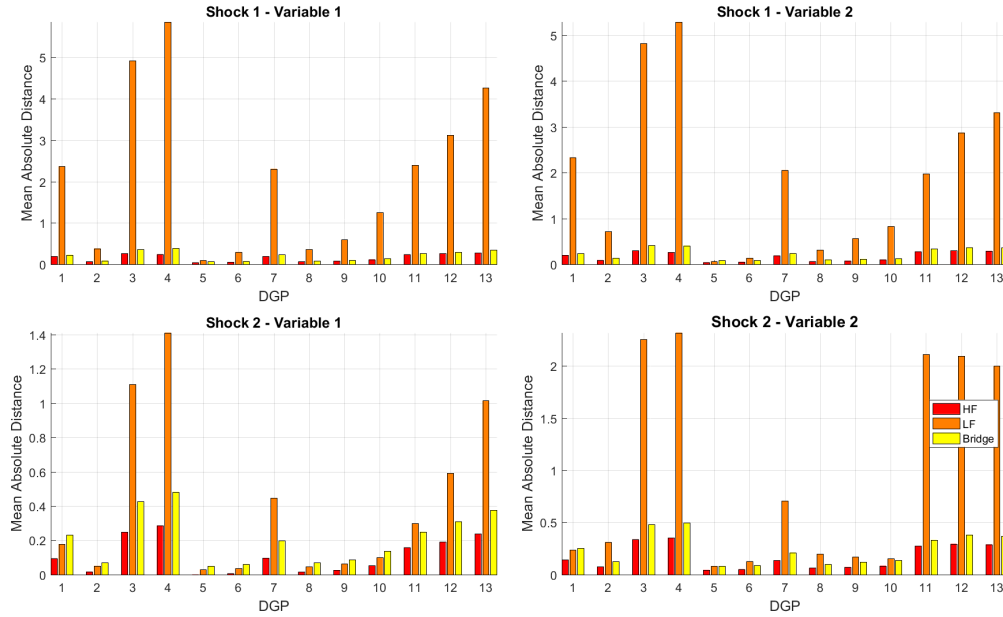
Notes: IRFs to a shock in the third variable (y) in the three variable system. Left panel - first variable (x); middle panel - second variable (z); right panel - third variable (y). The shock is identified through wrong a Cholesky in the HF system (blue), LF system (green) and Bridge Proxy (red). Shaded areas correspond to the 90% confidence bands. The black line is the true IRF. Time aggregation follows a skip-sampling scheme.

Figure C.7: MAD in the two variable system: wider frequency mismatch



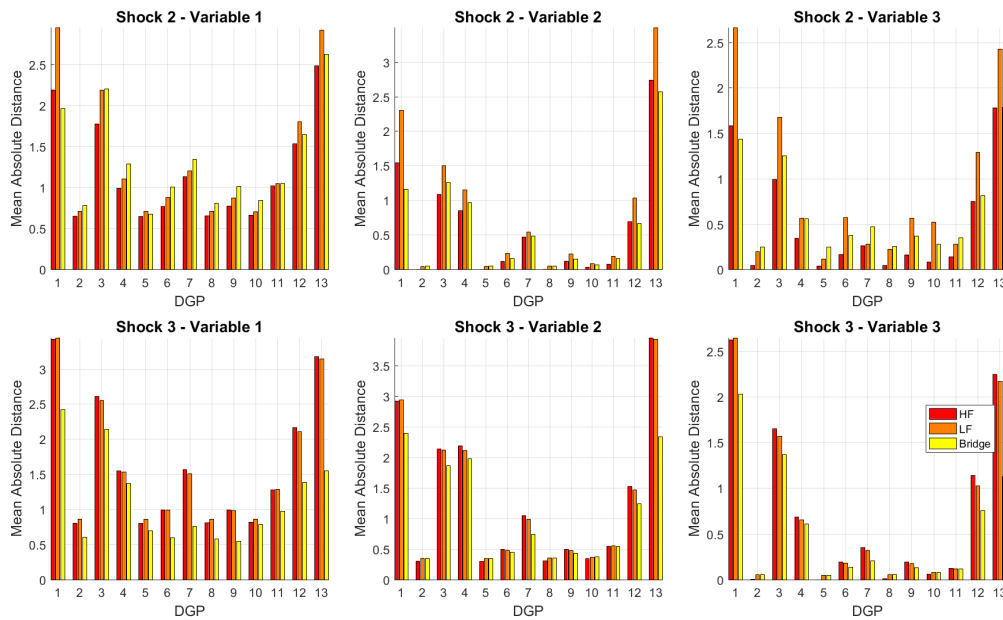
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR (through the correct recursive scheme). Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.8: MAD in the two variable system under measurement error



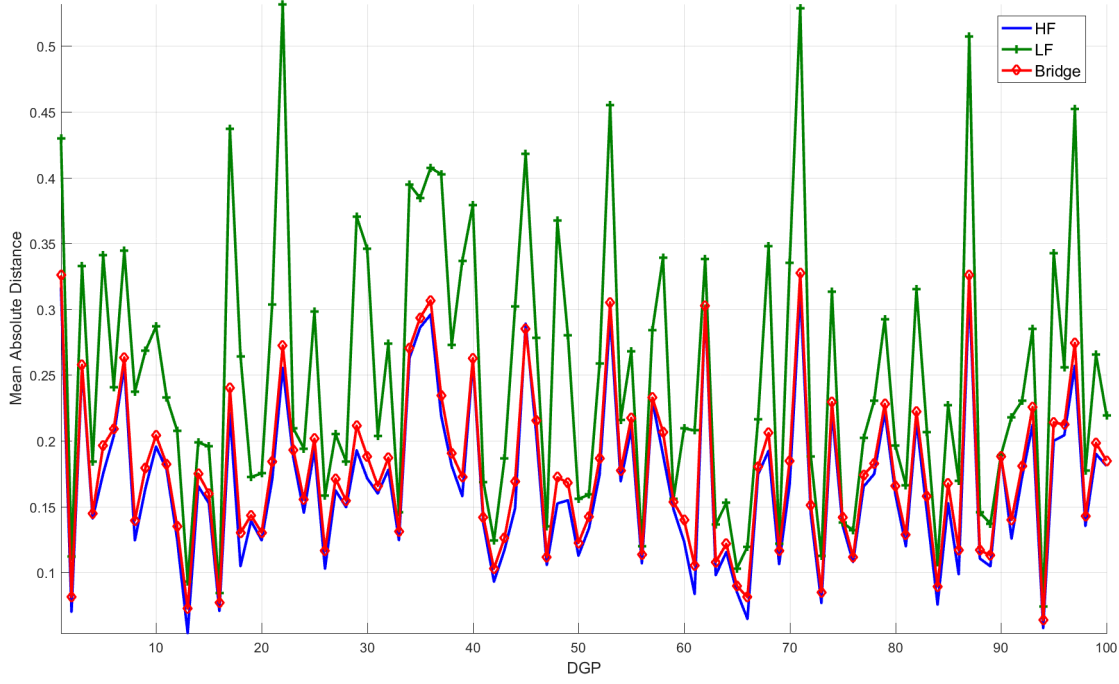
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR. Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.9: MAD in the practical case: the wrong high frequency



Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR. Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.10: MAD in each of the 100 large randomly parametrized systems



Notes: Mean Absolute Distance performances in the 100 randomly parametrized large systems of the HF-VAR, LF-VAR and Bridge Proxy-SVAR. The summary static is based on the percentage MAD between the true and estimated IRFs in each combination of shocks-variables in the system. Time aggregation follows a skip-sampling scheme.

C.3 Averaging Temporal Aggregation

C.3.1 An Illustrative Example

This section presents the same derivations of Section 3.2.3.1 but when time aggregation follows an averaging scheme. Averaging usually modifies the AR component in the same way as point-in-time sampling but induces higher order MA components.

$$\begin{aligned} Y_t &= AY_{t-1} + B\varepsilon_t & \varepsilon_t &\sim \mathcal{N}(0, \mathcal{I}) \\ (I - AL)Y_t &= B\varepsilon_t & \varepsilon_t &\sim \mathcal{N}(0, \mathcal{I}) \end{aligned} \quad (\text{C.13})$$

To move to the time aggregated representation under averaging, we first apply the filter $w(L) = I + L$ to transform the series as sum (average is just a linear transformation of it)

and then we skip-sample through $D(L) = I + AL$:

$$\begin{aligned}
 D(L)w(L)(I - AL)Y_t &= D(L)Bw(L)\varepsilon_t \\
 (I - A^2L^2)(I + L)Y_t &= (I + L)(I + AL)B\varepsilon_t \\
 Y_t + Y_{t-1} &= A^2(Y_{t-2} + Y_{t-3}) + B(\varepsilon_t + \varepsilon_{t-1}) + AB(\varepsilon_{t-1} + \varepsilon_{t-2}) \\
 Y_\tau &= CY_{\tau-1} + v_\tau \quad v_\tau \sim (0, BB' + (\mathcal{I} + A)BB'(\mathcal{I} + A)' + ABB'A') \\
 Y_\tau &= CY_{\tau-1} + B\xi_t + AB\xi_{t-1} \quad \xi_t \sim (0, \mathcal{I}), \text{corr}(\xi_t, \xi_{t-1}) = AB'B
 \end{aligned} \tag{C.14}$$

where $C = A^2$. Let us consider a bivariate system in extended notation:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix} \tag{C.15}$$

which is observed in time aggregation as

$$\begin{bmatrix} x_\tau \\ y_\tau \end{bmatrix} = \begin{bmatrix} a_{11}^2 + a_{12}a_{21} & a_{11}a_{12} + a_{12}a_{22} \\ a_{11}a_{21} + a_{21}a_{22} & a_{12}a_{21} + a_{22}^2 \end{bmatrix} \begin{bmatrix} x_{\tau-1} \\ y_{\tau-1} \end{bmatrix} + \begin{bmatrix} v_\tau^x \\ v_\tau^y \end{bmatrix} \tag{C.16}$$

where

$$\begin{bmatrix} v_\tau^x \\ v_\tau^y \end{bmatrix} = \begin{bmatrix} b_{11}(\varepsilon_t^x + \varepsilon_{t-1}^x) + (a_{11}b_{11} + a_{12}b_{21})(\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{12}b_{22}(\varepsilon_{t-1}^y + \varepsilon_{t-2}^y) \\ b_{21}(\varepsilon_t^x + \varepsilon_{t-1}^x) + b_{22}(\varepsilon_t^y + \varepsilon_{t-1}^y) + (a_{21}b_{11} + a_{22}b_{21})(\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{22}b_{22}(\varepsilon_{t-1}^y + \varepsilon_{t-2}^y) \end{bmatrix}$$

In this case, we employ as a proxy the first HF shock in the LF period to recover the true impact matrix. Namely, $z_\tau = \varepsilon_{t-1}^y$. The first stage in our IV procedure reads:

$$\begin{aligned}
 \hat{\beta}_{1s} &= \mathbb{E} [z_\tau' z_\tau]^{-1} \mathbb{E} [z_\tau' v_\tau^y] \\
 &= \frac{\mathbb{E} [\varepsilon_{t-1}^y \{b_{21}(\varepsilon_t^x + \varepsilon_{t-1}^x) + b_{22}(\varepsilon_t^y + \varepsilon_{t-1}^y)\}]}{\mathbb{E} [(\varepsilon_{t-1}^y)(\varepsilon_{t-1}^y)]} \\
 &\quad + \frac{\mathbb{E} [\varepsilon_{t-1}^y \{(a_{21}b_{11} + a_{22}b_{21})(\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{22}b_{22}(\varepsilon_{t-1}^y + \varepsilon_{t-2}^y)\}]}{\mathbb{E} [(\varepsilon_{t-1}^y)(\varepsilon_{t-1}^y)]} \\
 &= (b_{22} + a_{22}b_{22}) \\
 &= b_{22}(1 + a_{22})
 \end{aligned} \tag{C.17}$$

and the fitted values are

$$\hat{\beta}_{1s} z_\tau = b_{22} (1 + a_{22}) \varepsilon_{t-1}^y$$

The second stage regression reads

$$\xi_\tau^x = \beta_{2s} \left(\hat{\beta}_{1s} z_\tau \right) + \varphi_\tau \quad \varphi_\tau \sim WN$$

$$\begin{aligned} \hat{\beta}_{2s} &= \mathbb{E} \left[\left(\hat{\beta}_{1s} z_\tau \right) \hat{\beta}_{1s} z_\tau \right]^{-1} \mathbb{E} \left[\hat{\beta}_{1s} z_\tau v_\tau^x \right] \\ &= \left(\hat{\beta}_{1s} \right)^{-1} \mathbb{E} [z_\tau z_\tau]^{-1} \mathbb{E} [z_\tau \xi_\tau^x] \\ &= \left(\hat{\beta}_{1s} \right)^{-1} \mathbb{E} [\varepsilon_{t-1}^y \{ b_{11} (\varepsilon_t^x + \varepsilon_{t-1}^x) + (a_{11} b_{11} + a_{12} b_{21}) (\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{12} b_{22} (\varepsilon_{t-1}^y + \varepsilon_{t-2}^y) \}] \\ &= \frac{a_{12} b_{22}}{b_{22} (1 + a_{22})} \\ &= \frac{a_{12}}{1 + a_{22}} \end{aligned} \tag{C.18}$$

We obtain an equivalent result if we apply straight the definition of *IV* estimator:

$$\begin{aligned} \hat{\beta}_{Proxy} &= \mathbb{E} [z_\tau v_\tau^y]^{-1} \mathbb{E} [z_\tau v_\tau^x] \\ &= \frac{\mathbb{E} [\varepsilon_{t-1}^y \{ b_{11} (\varepsilon_t^x + \varepsilon_{t-1}^x) + (a_{11} b_{11} + a_{12} b_{21}) (\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{12} b_{22} (\varepsilon_{t-1}^y + \varepsilon_{t-2}^y) \}]}{\mathbb{E} [\varepsilon_{t-1}^y \{ b_{21} (\varepsilon_t^x + \varepsilon_{t-1}^x) + b_{22} (\varepsilon_t^y + \varepsilon_{t-1}^y) + (a_{21} b_{11} + a_{22} b_{21}) (\varepsilon_{t-1}^x + \varepsilon_{t-2}^x) + a_{22} b_{22} (\varepsilon_{t-1}^y + \varepsilon_{t-2}^y) \}]} \\ &= [b_{22} (1 + a_{22})]^{-1} a_{12} b_{22} \\ &= \frac{a_{12}}{1 + a_{22}} \end{aligned} \tag{C.19}$$

It is important to highlight that, even if we are able to recover the true *IRFs* on impact, the estimated autoregressive matrix of the LF-VAR is biased due to the VARMA structure of the temporally aggregated process.³ VARMA models are not used in empirical application due the high parametrization and severe problems in defining an economic interpretable structure (SVARMA). Therefore, we do not tackle this issue as the improvement in identification over a LF-VAR is the best we can reach through our methodology. This steams from the fact that we derive identifying restrictions at HF but we still rely on the LF-VAR representation for the transmission of the shocks. On the contrary, the state space MF-VAR improves the estimates of the *A* matrix by shifting the representation of the LF variables at HF.

³The bias in the estimated *A* matrix induces a bias also in the estimated reduced form residuals. However, the IRFs on impact (*B*) would be biased only if the bias in the *A* matrix were correlated with the structural shocks. In a simple AR(1) process, the bias is a constant and so does not interfere with the estimates of the *B* matrix. Moreover, our simulations of more complex processes indicate that the *Bridge* always recover the impact response.

C.3.2 Comparison *Bridge* - Mixed Frequency VAR

If financial processes are part of the analysis, the shortcoming of the MF-VAR consists of the inability to use daily data.⁴ To the best of our knowledge, the MF-VAR can exploit at most weekly data. Therefore, there is a trade-off between the identification of the impact matrix B , favorable to the *Bridge*, and the estimates of the autoregressive matrix A , favorable to the MF-VAR.⁵ Finally, notice that sample size is quite relevant in this trade-off: the biases in the estimate A matrix are decreasing in the sample size as the VARMA process is well approximate by a VAR in large samples but not in short samples.⁶

We design two Monte Carlo experiments to compare the performances of the *Bridge* versus the MF-VAR. On the one hand, we quantitatively illustrate this trade-off. On the other hand, and more importantly, our goal is to study the dependence of the relative performances of the two methodologies on the parametrization of the DGP. Our intuition suggests that when the variables in the system are very responsive to other shocks on impact, i.e. the simultaneity problem is very severe, improving the estimation of the impact matrix is crucial.

We consider both a full information and partial information setup. In the full information case, the *Bridge* employs all variables in both stages, whereas the MF-VAR is actually the counter-factual HF-VAR. In the partial information case, we run the practical case presented in Section 3.3.3. The first variable in the system is effectively unobservable at HF, so the *Bridge* employs only two variables in recovering the shocks at HF (first stage). The MF-VAR estimates in a state space representation the missing observations of the LF variable.

Full Information We employ a nine variable system to quantitatively evaluate the A - B trade-off, but we study also a two variable system to illustrate how this trade-off depends on simultaneity. The true frequency of the process is daily but macro variables are available only at the monthly frequency. We compare the best performances of a MF-VAR (HF-VAR) on weekly data with the best performances of the *Bridge* (full information) using daily

⁴For example, in a quarterly-weekly ($m = 12$) Monte Carlo simulation [Foroni and Marcellino \(2016\)](#) report:

1. "For computational reasons (the number of missing values is high and therefore the computational time increases substantially), we fix the number of replications to $R = 500$."
2. "Due to the higher number of missing values when $m = 12$, we increase the size to 300 quarterly observations to obtain more stable results when running the Kalman filter."

⁵If the true process occurs at daily frequency while the MF-VAR employs weekly data, the estimates of the A matrix will still be biased, even if less than the monthly estimates.

⁶Notice that, on the one hand, the strength of the instrument and the precision of the estimates is increasing with the sample size for the *Bridge*. On the other hand, the computational burden of the MF-VAR increases with the length of the sample.

as HF data and monthly as LF data. Once again, we run a 100 random parametrization experiment in a three variable system as we want to analyze the trade-off between *Bridge* (advantage in identifying the impact matrix) versus MF-VAR (advantage in estimating the autoregressive matrix). We do not constrain the generated parameter in anyway other than maintaining a mapping variables-shocks. Overall, we obtain the results displayed in Table C.2.

More importantly, for the bivariate case we build an index of relative performances for the cross impacts of the shocks and regress it on the parameters of the B matrix. Our index capture the percentage difference in the MAD between the MF-VAR and *Bridge*. Table C.3 confirms our priors: when the off-diagonal elements in the B matrix are large, the (daily-monthly) *Bridge* is preferred to the (weekly) MF-VAR.

Table C.2: Performance comparison in Monte Carlo simulations - Bridge and MF-VAR

Identification	MAD GAINS OVER LF-VAR (MONTHLY)
<u>Bivariate system</u>	
MF-VAR (HF-VAR weekly)	70.6%
<i>Bridge</i> (full-information daily)	78.7%
<u>9 variable randomized system</u>	
MF-VAR (HF-VAR weekly)	67.4%
<i>Bridge</i> (full-information daily)	66.2%

Notes: Performance comparison across the MF-VAR (weekly HF-VAR), the LF-VAR (monthly) and the (full information) *Bridge* Proxy-SVAR (daily-monthly). Performances are evaluated in terms of the Mean Absolute Distance (MAD) between the true IRFs and the estimated IRFs. The gains are expressed as percentage MAD gains over the LF-VAR. We report the results for I) the bivariate case used to evaluate the dependence of the performances on the structure of the DGP; II) a 9 variable randomly parametrized system in 100 randomly parametrized DGPs.

Table C.3: MAD comparison as function of DGP: full information

Variable	% Δ MAD MF-B			
	(1) OLS	(2) OLS	(3) Probit	(4) Probit
	Var 2-Shock 1	Var 1-Shock 2	Var 2-Shock 1	Var 1-Shock 2
$ b_{12} $	0.40*** (0.13)	-0.25 (0.18)	1.07*** (0.27)	0.93* (0.49)
$ b_{21} $	-0.05 (0.12)	0.47*** (0.17)	-0.31 (0.23)	0.51 (0.38)
Constant	-0.19 (0.15)	1.10*** (0.21)	-0.73*** (0.28)	0.39 (0.38)
Observations	100	100	100	100
R-squared	0.09	0.09	0.14 (pseudo)	0.11 (pseudo)

Notes: Relationship between relative performances of the (daily-monthly) *Bridge* over the (weekly) MF-VAR and the structure of the impact matrix. In particular, we study the relationship between the estimated cross IRFs with the absolute values of the off-diagonal elements in the B matrix: b_{12} and b_{21} . The higher the degree of simultaneity, the wider the gains from using daily data (*Bridge*) over weekly data (MF-VAR). Standard errors in parenthesis *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Partial Information We turn next to a three variable system where one variable is actually unobserved a HF and compare how the MF-VAR and *Bridge* cope with this lack of information. The LF variable is observable only once each 24 periods as average.⁷ The MF-VAR aggregates the HF over 8 periods and jointly estimate the relationship with the LF variable. Basically, the MF-VAR reverse to the monthly-quarterly case. Finally, the *Bridge* recovers shocks at the true frequency by using a bivariate system with the two variables available at HF. In terms of MAD percentage gains over the LF-VAR, the MF-VAR improves by 46.7%, while the *Bridge* by 70.5%.

However, more than providing a quantitative comparison across the two methodologies, we are interested in analyzing the cases that suit one or another procedure. As in the previous case, we regress the relative performances of the *Bridge* versus the MF-VAR on the parametrization of the B matrix. In particular, we focus on the simultaneity between the variables observable at the highest frequency. We analyze how this simultaneity affects the bias in the estimated responses of the low frequency variable to the high frequency shocks. Namely, we regress the bias in the *IRF* of variable x to shocks in z and y on b_{23} and b_{32} .⁸ The results presented Table highlight that the gains from using the *Bridge* increasing in the simultaneity across the high frequency variable. This finding suggests that the *Bridge* is particularly suitable to study macro-financial linkages where high frequency variables contemporaneous co-move significantly.

⁷This number may be interpreted as the working days within one month.

⁸We include b_{22} and b_{33} to take into account the size of the shock.

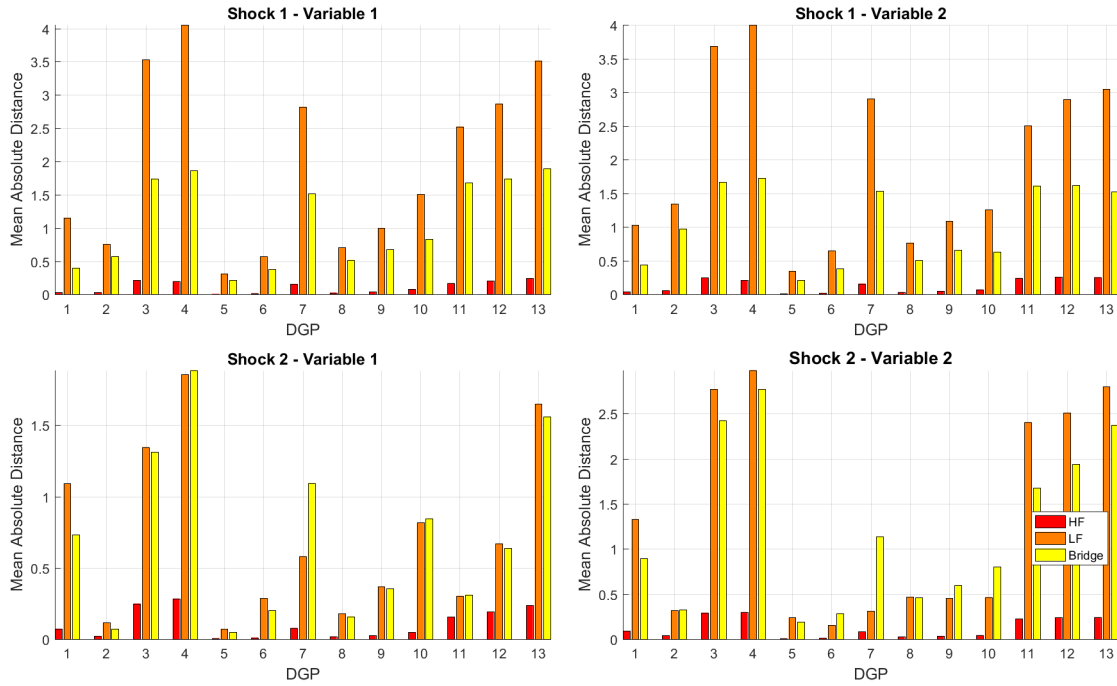
Table C.4: MAD comparison as function of DGP: partial information

Variables	% Δ MAD MF-Bridge	
	(1)	(2)
	Var 1-Shock 2	Var 1-Shock 3
$ b_{32} $	2.49** (1.15)	2.13* (1.27)
$ b_{23} $	-0.63 (1.18)	2.22* (1.27)
$ b_{33} $	0.71 (1.01)	-0.99 (1.08)
$ b_{22} $	-0.86 (0.81)	0.034 (0.91)
Constant	1.49 (1.84)	0.39 (1.99)
Observations	99	96
R-squared	0.058	0.074

Notes: Relationship between relative performances of the (daily-monthly) Bridge over the (weekly) MF-VAR and the structure of the impact matrix. In particular, we study the relationship between the estimated cross IRFs with the absolute values of the off-diagonal elements in the B matrix: b_{23} and b_{32} . These two parameters represent the degree of simultaneity between variable 2 (z) and variable 3 (y). The higher the degree of simultaneity, the wider the gains from using daily data (Bridge) over weekly data (MF-VAR).

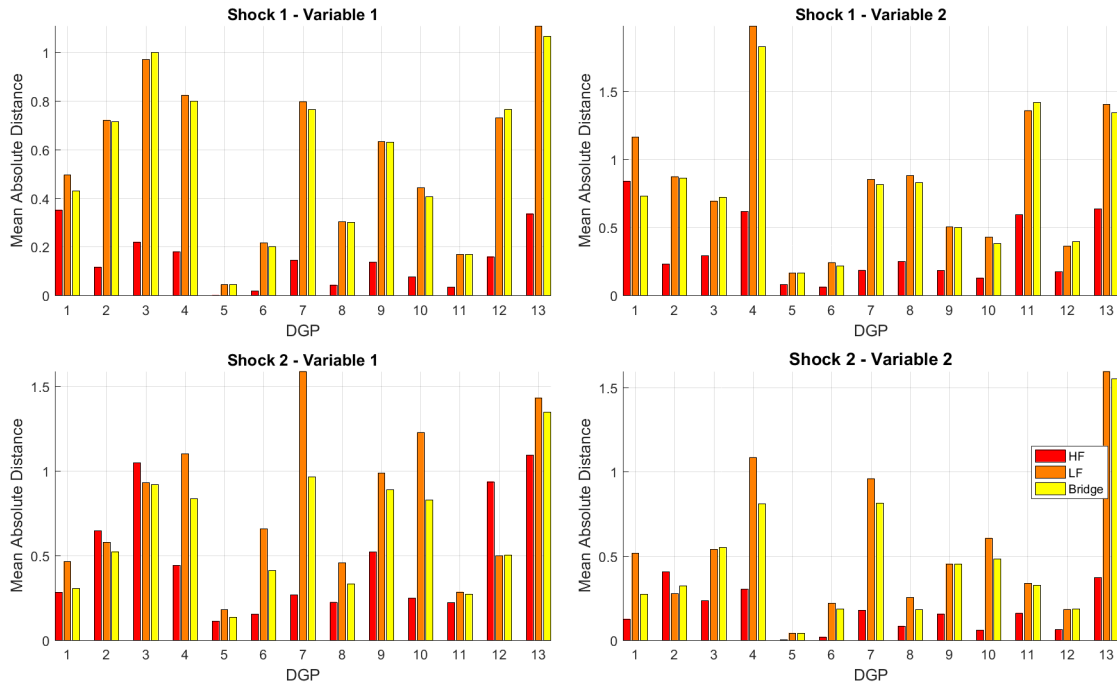
C.3.3 Monte Carlo Simulations - Averaging Case

Figure C.11: MAD in the two variable system - averaging



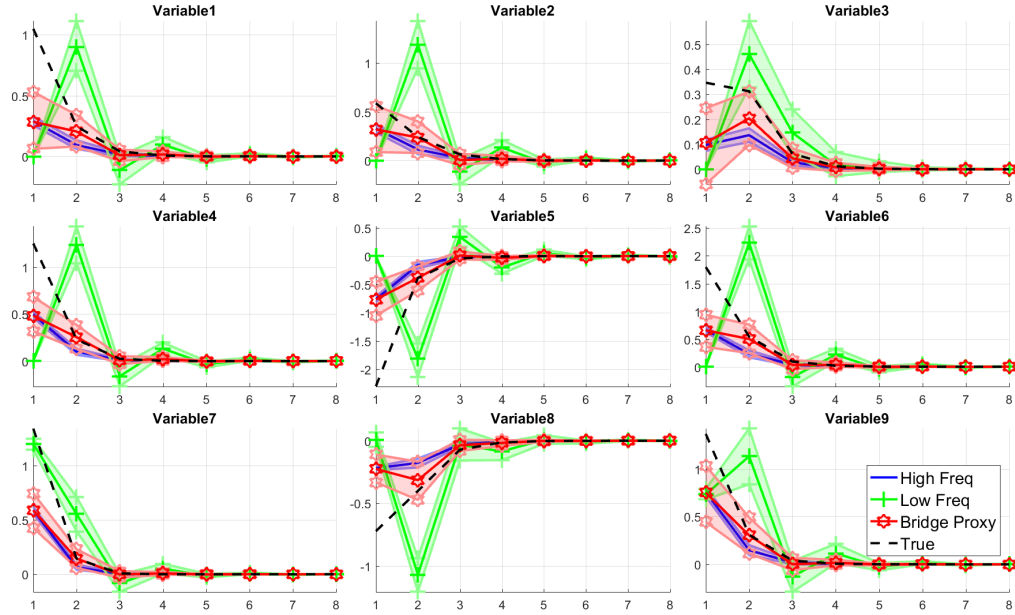
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR (through the correct recursive scheme). Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows an averaging scheme.

Figure C.12: MAD in the two variable system: misspecification - averaging



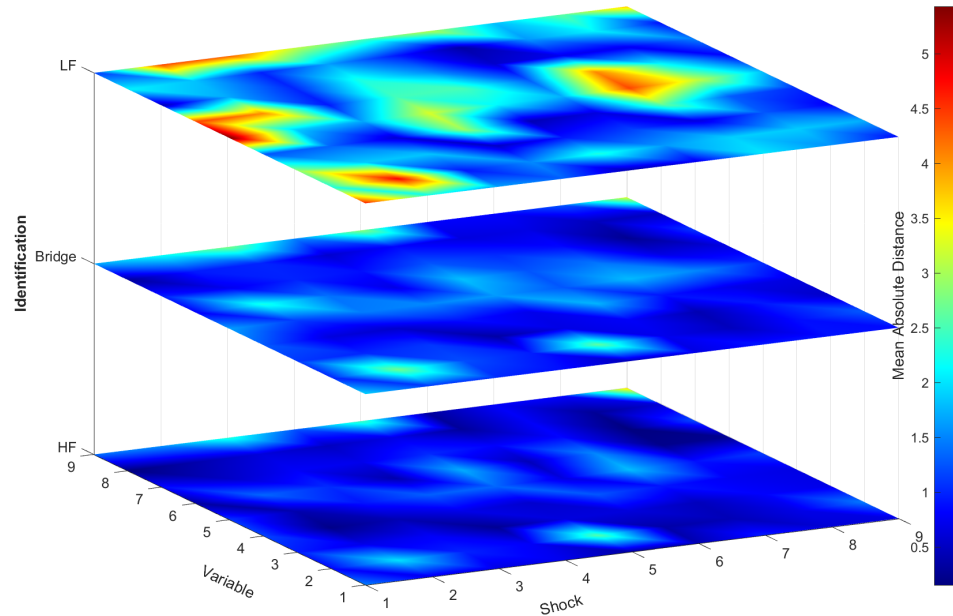
Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR. Results are reported for 13 parametrization of the DGP. The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.13: IRFs from large randomized Monte Carlo experiment - averaging



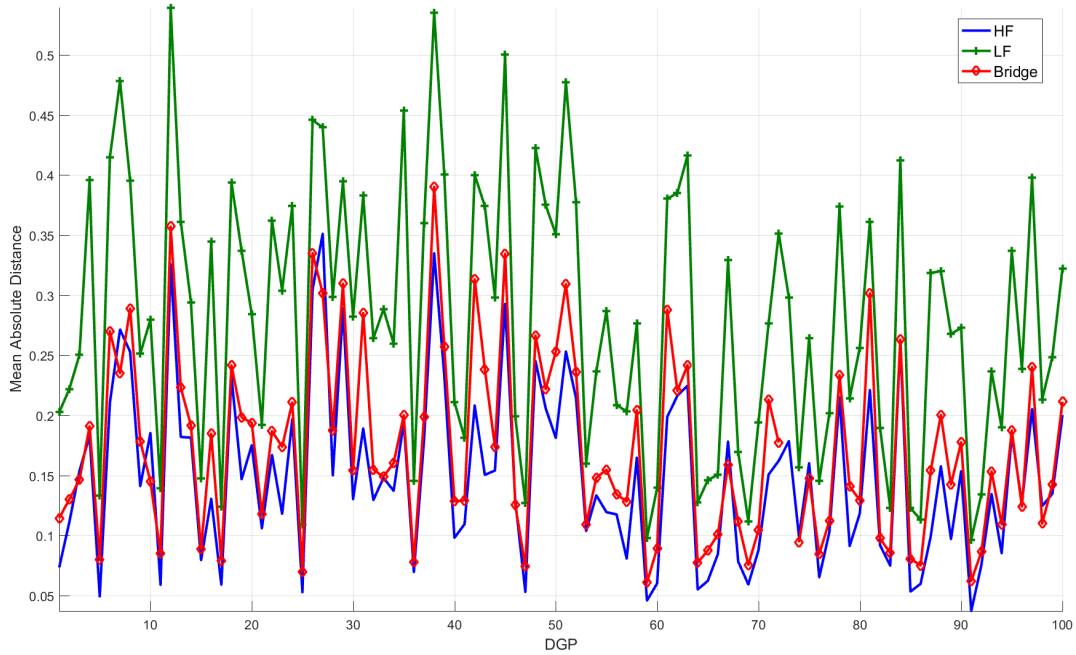
Notes: Example of the IRFs of the system to a shock in the first variable in the system, estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR in one of the 100 randomly parametrized DGPs. Shaded areas correspond to the 90% confidence bands across 1000 replications. The true IRF is represented by the dotted black line. Time aggregation follows an averaging scheme.

Figure C.14: MAD heatmap from large randomized Monte Carlo experiment - averaging



Notes: Mean Absolute Distance (MAD) between the true IRFs and the IRFs estimated by the HF-VAR, LF-VAR and Bridge Proxy-SVAR in one of the 100 randomly parametrized DGPs. Results are reported for each combination of shocks-variables in the system (81). The MAD is computed by averaging the MAD over the 1000 replications. Time aggregation follows a skip-sampling scheme.

Figure C.15: MAD in each of the 100 large randomly parametrized systems

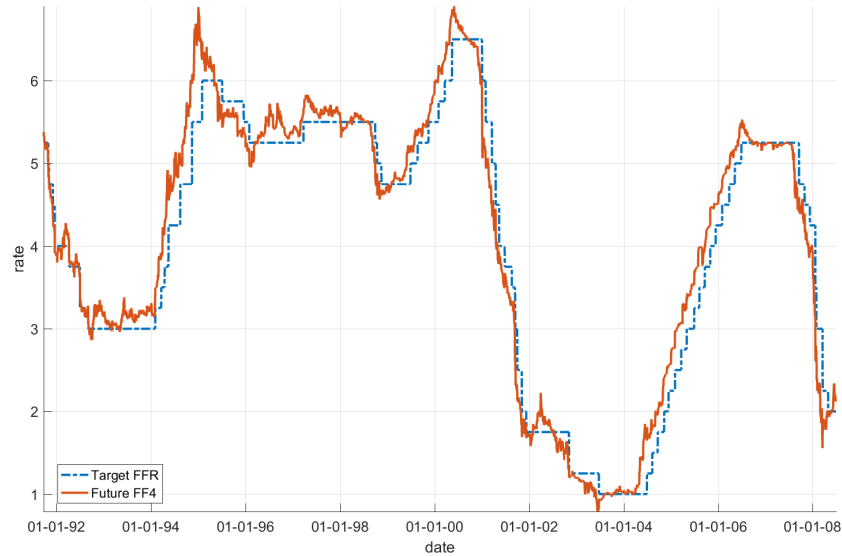


Notes: Mean Absolute Distance performances in the 100 randomly parametrized large systems of the HF-VAR, LF-VAR and Bridge Proxy-SVAR. The summary static is based on the percentage MAD between the true and estimated IRFs in each combination of shocks-variables in the system. Time aggregation follows a skip-sampling scheme.

C.4 Empirical Application

Name	Datastream Code
Fed Funds Future 3 months ahead	CFFCS30
S&P 500	S&PCOMP
Oil Price Index	OILBREN
Oil Price Future 3 months ahead	NCLCS30
BBA Corporate Spread	LHIGBAA
Dollar-Euro Exchange Rate	USEURSP
Dollar-Sterlin Exchange Rate	USDOLLR
Commodity Price Index	CRBSPOT
Gold Price Index	GOLDHAR
Oil Future 3 months ahead	NCLCS30
Eurodollar Future 3 months ahead	NCLCS30
Cleveland Financial Stress Index	USCVFSI
CBOE VIX - Stock Volatility Index	CBOEVXO
Bid Cover Ratio in Treasuries Auctions (26 weeks)	USBCR26
Bank of America Merrill Lynch Asset Backed Security Index	MLR0A2L
US Federal Funds Target Rate	USFDTRG
US Treasury Term Premia 1 years	USTTP1Y
US Treasury Term Premia 5 years	USTTP5Y
US Treasury Term Premia 10 years	USTTY10
Conventional Fixed Mortgage Rate	FRCMORT

Table C.5: Data description

Figure C.16: Comparison TFFR and FF4

Notes: Comparison Target Fed Fund Rate - Fed Fund Rate Future 3 month ahead

C.4.1 Shocks identified from the Daily VAR

C.4.1.1 Baseline Identification

Table C.6-C.7 point out that, even without imposing any particular role for the FOMC meeting days, our conservative identification highlights a special role for these days. In fact, both mean and standard deviation of the shocks on FOMC meeting days are twice as sizable as the same statistics computed over the whole sample. Not surprisingly, this difference is more relevant for future contracts at shorter horizons. More formally, we also regress the size of the shocks over a dummy that reflect the FOMC meeting days, finding the same pattern (Table C.8).

Finally, we provide anecdotal evidence on the identified shocks. Specifically, the daily framework allows us to track the events that occurred on the days in which we register the most sizable shocks. Description and references are included in Table C.9.

Table C.6: Descriptive statistics of monetary policy shocks - comparison across maturities

Variable	Mean	Std. Dev.	Min.	Max.
TFFR*	0.444	0.838	0	15.136
fut4*	0.6	0.747	0	10.156
fut1	0.53	0.79	0	15.973
fut4	0.598	0.739	0	10.151
fut7	0.614	0.726	0	8.268
fut18	0.559	0.769	0	15.361
Observations	4352			

Notes: Shocks in the whole sample - * refers to section 3.4.1; others show the robustness to using different future contracts (over a slightly shorter sample).

Table C.7: Descriptive statistics of monetary policy shocks on FOMC meeting dates - comparison across maturities

Variable	Mean	Std. Dev.	Min.	Max.
TFFR*	2.832	3.422	0.015	15.136
fut4*	1.139	1.303	0.01	7.184
fut1	1.092	1.346	0.002	9.587
fut4	0.856	0.969	0.008	6.524
fut7	0.813	0.930	0.001	7.104
fut18	0.765	0.841	0.011	5.966
Observations	148			

Notes: Shocks in the FOMC dates - * refers to section 3.4.1; others show the robustness to using different future contracts (over a slightly shorter sample).

Table C.8: Regression of monetary policy shocks on FOMC meeting dates dummy - comparison across maturities

VARIABLES	(1) TFFR*	(2) fut4*	(3) fut1	(4) fut4	(5) fut7	(6) fut18
FOMC	2.47*** (0.06)	0.56*** (0.06)	0.58*** (0.07)	0.27*** (0.06)	0.21*** (0.06)	0.21*** (0.06)
Constant	0.36*** (0.01)	0.58*** (0.01)	0.51*** (0.01)	0.59*** (0.01)	0.61*** (0.01)	0.55*** (0.01)
Observations	4,352	4,352	4,352	4,352	4,352	4,352
R-squared	0.29	0.02	0.02	0.00	0.00	0.00

Standard errors in parentheses

*** p<0.01

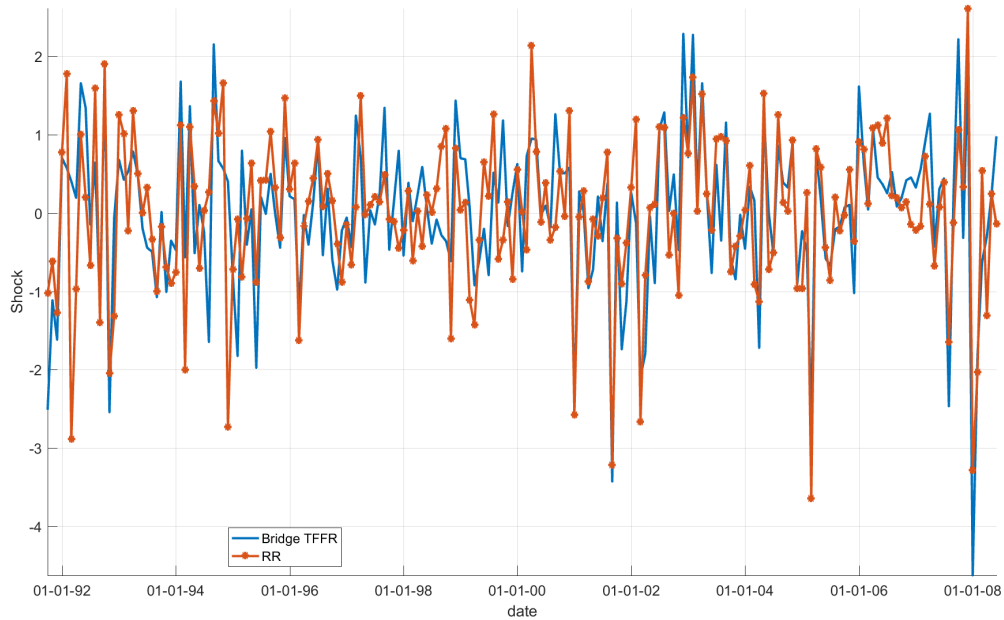
Notes: Daily shocks regressed on FOMC days dummy - * refers to Section 3.4.1; others show the robustness to using different future contracts (over a slightly shorter sample).

Table C.9: Largest monetary policy shocks

Bridge TFFR	Event 1	Event 2	Event 3
Dates	18 March 2008	22 January 2008	15 November 1994
Description	FOMC meeting	FOMC meeting	FOMC meeting
Reference	Event 1a; Event 1b	Event 2a; Event 2b	Event 3
Shock	−15 <i>std</i>	−13.1 <i>std</i>	15.9 <i>std</i>
Bridge FF4	Event 1	Event 2	Event 3
Dates	02 January 2001	22 January 2008	02 January 1995
Description	Anticipation FOMC 03 Jan 2001	FOMC meeting	\$50 billion bailout Mexican <i>tequila crisis</i>
Reference	Event 1	Event 2a Event 2b	Event 3
Shock	−7.9 <i>std</i>	−7.5 <i>std</i>	10.5 <i>std</i>

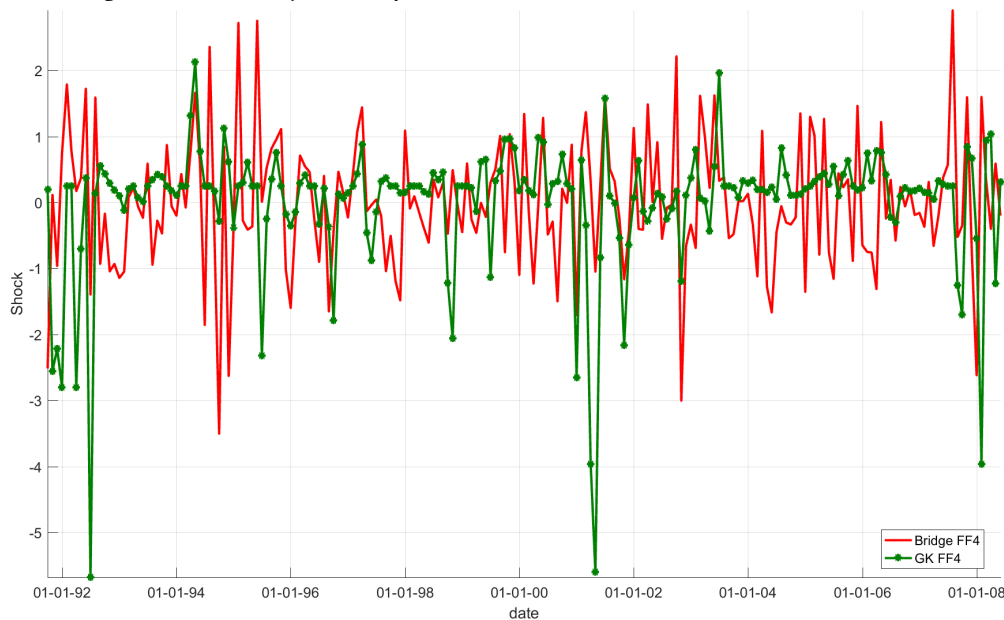
Notes: Main shocks (reported in standard deviation units) identified in our daily VAR and corresponding events - section 3.4.1

Figure C.17: Comparison of TFFR shocks with Romer and Romer shocks



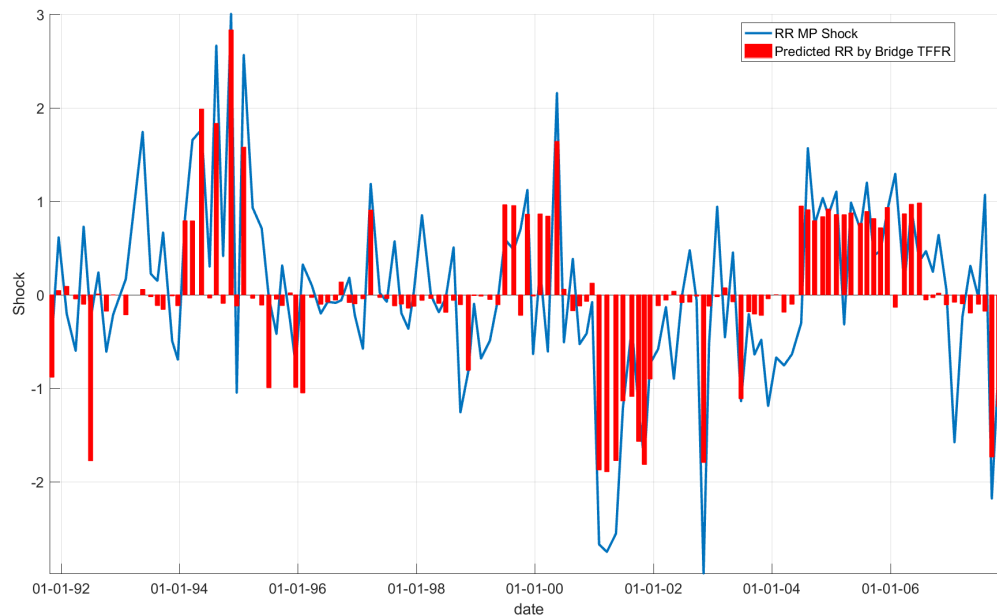
Notes: Comparison of monetary policy shocks from different identifications. Bridge TFFR (blue) refers to the series of shocks identified using our daily VAR. RR refers to the series of shocks build as [Romer and Romer \(2004\)](#), extended by [Coibion, Gorodnichenko, Kueng, and Silvia \(2012\)](#).

Figure C.18: Comparison of FF4 shocks with Gerter and Kararadi shocks



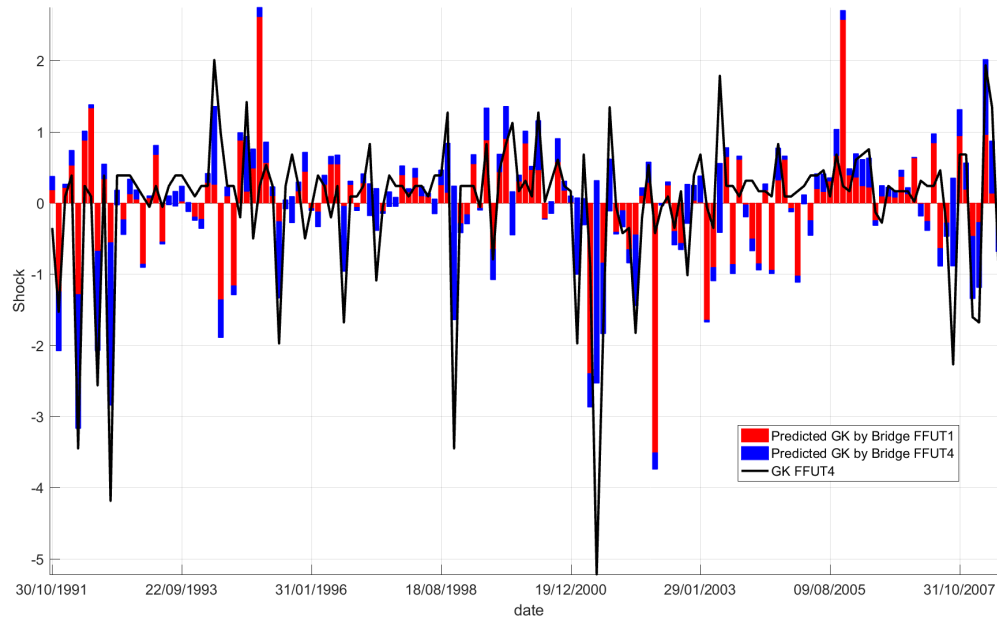
Notes: Comparison of monetary policy shocks from different identifications. Bridge FF4 (red) refers to the series of shocks identified using our daily VAR. GKFF4 refers to the series of shocks employed by [Gertler and Karadi \(2015\)](#).

Figure C.19: Explanatory power of TFFR shocks for Romer and Romer shocks



Notes: [Romer and Romer \(2004\)](#) shocks, extended by [Coibion, Gorodnichenko, Kueng, and Silvia \(2012\)](#), fitted by your TFFR series of shocks estimated in a daily VAR.

Figure C.20: Explanatory power of TFFR and FF4 shocks for Romer and Romer shocks



Notes: [Gertler and Karadi \(2015\)](#) FF4 shocks fitted by your TFFR and FF4 shocks estimated in a daily VAR.

C.4.1.2 Alternative Identifications

Our two alternative identification strategies yield series of daily monetary policy shocks that are very correlated with our baseline series. Moreover, they generate very similar

macroeconomic effects. In Tables C.10-C.11 we report the correlations among the shocks identified with all the strategies that we have employed.

Identification Via Heteroskedasticity

In short, the identification proposed by [Rigobon \(2003\)](#) exploits the change in the volatility of the structural shocks across (at least) two regimes. Consistently with our finding reported in Table C.6-C.7, we assume that the variance of the monetary policy shocks changes across FOMC meeting days and non-FOMC meeting days. We estimate a bivariate VAR including FF4 and SP&500 and exploit the change in the variance of the shocks in FF4 across the two regimes for identification. In this way, we obtain a series of shocks that correlates 0.9998 with the shocks identified by ordering the TFFR last in our large scale VAR. The same result hold in three and four variable daily VARs, which additionally include the commodity price index and commodity price index plus the Cleveland Financial Stress index. Finally, notice that event-based identification is equivalent to the identification via heteroskedasticity where the change in the volatility across the two regimes is assumed to be infinite.

Identification Via Independent Component Analysis

Detailed reference on the application of Independent Component Analysis (ICA) to VARs can be found in [Capasso and Moneta \(2016\)](#) and [Gourieroux, Monfort, and Renne \(2017\)](#). Intuitively, ICA can be seen as a generalization of principal component analysis (PCA). While PCA looks for uncorrelated latent components, ICA minimizes the statistical independence among such components. Obviously, if the data is normally distributed, the two concept are equivalent. However, when departing from gaussianity, ICA can solve the identification problem in VARs. While the reduced form residuals can be decomposed in uncorrelated structural shocks in infinite ways, ICA searches for the (unique) combination of the most statistically independent components.

Both visual inspection and the Kolmogorov-Smirnov reject the normality of the 18 reduced form residuals in our daily VAR. We do not assume any particular distribution of the reduced form residuals but we estimate semi-parametrically the independent components.⁹ We consider as monetary policy shock the structural shock that contributes the most to the variance of the FF4 on impact. The resulting series of structural shocks correlates 0.89 with the shocks in the TFFR and 0.9 with the shocks in the FF4 identified with our baseline recursive ordering.

⁹We employ the algorithm *Icasso* v1.22 and *FastICA* v2.5.

Table C.10: Correlation among monetary policy shocks across different identifications - daily frequency

	Target FFR - Last	FF4 - Last	FF4 - Heteroschedasticity	FF4 - ICA
Target FFR - Last	1	*	*	*
FF4 - Last	0	1	*	*
FF4 - Heteroskedasticity	1*	0	1	*
FF4 - ICA	0	0.92*	0	1

Notes: Correlations among monetary policy shocks recovered at the daily frequency through different identification strategies: 1) Target FFR ordered last in recursive identification; 2) Fed Future (3 months ahead) ordered last in recursive identification; 3) Fed Future (3 months ahead) exploiting the change volatility in FOMC meeting days and other days (heteroskedasticity); 4) Fed Future (3 months ahead) exploiting the non-normality of the reduced form residuals (Independent Component Analysis - ICA) . All coefficients different from 0 are statistically significant at the 1% level.

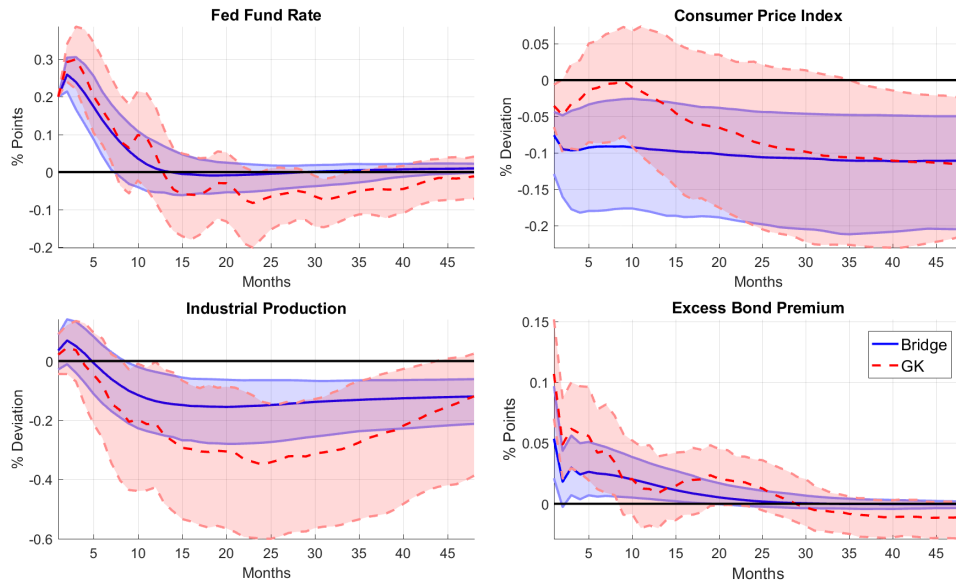
Table C.11: Correlation among monetary policy shocks across different identifications - monthly frequency

	Target FFR - Last	FF4 - Last	FF4 - Heteroschedasticity	FF4 - ICA
Target FFR - Last	1	*	*	*
FF4 - Last	0.1	1	*	*
FF4 - Heteroskedasticity	1 *	0.11	1	*
FF4 - ICA	0.1	0.93*	0.11	1

Notes: Correlations among monetary policy shocks recovered at the daily frequency through different identification strategies and aggregated at the monthly frequency: 1) Target FFR ordered last in recursive identification; 2) Fed Future (3 months ahead) ordered last in recursive identification; 3) Fed Future (3 months ahead) exploiting the change volatility in FOMC meeting days and other days (heteroskedasticity); 4) Fed Future (3 months ahead) exploiting the non-normality of the reduced form residuals (Independent Component Analysis - ICA) . * denotes statistical significance at the 1% level.

C.4.1.3 Impulse Response Functions

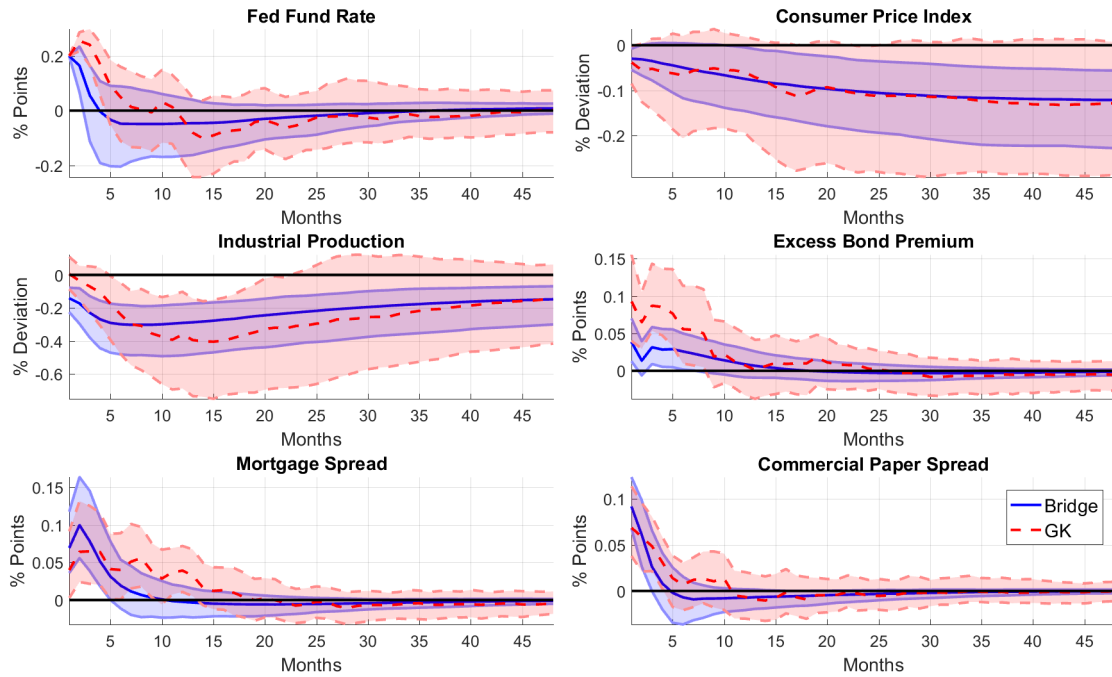
Figure C.21: IRFs FF4



Notes: IRFs to a monetary policy shock identified using Bridge Future using all the available days (FOMC and non-FOMC). From the first stage, $F - stat = 7.7$. The VAR is estimated in log-levels with the optimal number of lags (2) and includes a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands.

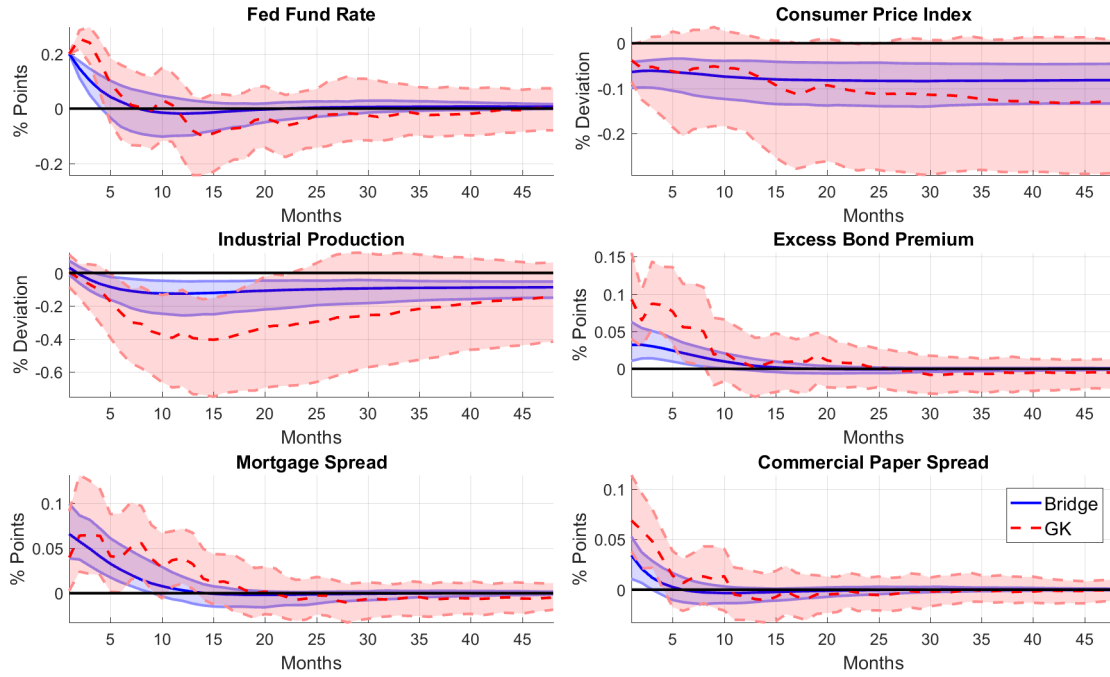
IRFs in the Medium System of Gertler and Karadi

Figure C.22: IRFs TFFR - medium system



Notes: IRFs to a monetary policy shock identified using Bridge Target. From the first stage, $F - stat = 10.2$. The VAR includes [FFR, CPI, Industrial Production, Excess Bond Premium, Mortgage Spread, Commercial Paper Spread] and it is estimated in log-levels with the optimal number of lags (2) and includes a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands from 1000 replications.

Figure C.23: IRFs FF4 - medium system



Notes: IRFs to a monetary policy shock identified using Bridge Future (FOMC and non-FOMC). From the first stage, $F - stat = 7.44$. The VAR includes [FFR, CPI, Industrial Production, Excess Bond Premium, Mortgage Spread, Commercial Paper Spread] and it is estimated in log-levels with the optimal number of lags (2) and includes a deterministic constant. Shaded areas correspond to 95% bootstrapped confidence bands.

Appendix D

Appendix: Chapter 4

D.1 Data

Table D.1: Data Sources

	Italy	Spain
Unemployment	ISTAT	Ministry of Economy
Industrial Production	ISTAT	INE
CPI Inflation	ISTAT	INE
Central Government Debt	Bank of Italy	Ministry of Economy
ECB Repo	ECB	ECB
M2	Bank of Italy	Banco de España
Consumer Confidence	ISTAT	Ministry of Economy
Business Confidence	ISTAT	Ministry of Industry
Volatility Index	ASR-Absolute Strategy	VSTOXX
CDS	Thomson Reuters CDS	Thomson Reuters CDS
Bid-Ask Spread	Bloomberg	Bloomberg
Yield Spread	ECB	ECB
Stock Prices	FTSE MIB	IBEX 35

	France	Germany
Unemployment	INSEE	OECD
Industrial Production	INSEE	Federal Statistical Office
CPI Inflation	Thomson Reuters	Thomson Reuters
Central Government Debt	Banque de France	Deutsche Bundesbank
ECB Repo	ECB	ECB
M2	Banque de France	Deutsche Bundesbank
Consumer Confidence	DG ECFIN	DG ECFIN
Business Confidence	DG ECFIN	DG ECFIN
Volatility Index	Euronext Paris	Deutsche Boerse
CDS	Thomson Reuters CDS	Thomson Reuters CDS
Bid-Ask Spread	Bloomberg	Bloomberg
Yield Spread	ECB	ECB
Stock Prices	CAC 40	MDAX Frankfurt

All the variables are seasonally adjusted originally or by using the X-13ARIMA procedure. We deflate nominal variables by the corresponding CPI price index in order to estimate the VAR with real variables.

In Section 4.4.2, we refer to the following questions from the Bank and Lending Survey:

1. *Firm Δ Standards*: Changes in bank's credit standards for approving loans or credit lines to enterprises, Overall (all firms and types of loans), Past three months.
2. *Firm: Costs-Asset Position*: Changes in the contribution of cost of funds and balance sheet constraints (costs related to bank's capital position) affecting credit standards for approving loans or credit lines to enterprises.
3. *Firm: Liquidity Position*: Changes in the contribution of cost of funds and balance sheet constraints (bank's liquidity position) affecting credit standards for approving loans or credit lines to enterprises.
4. *Firm: Risk-Economic Activity*: Changes in the contribution of perception of risk about general economic situation and outlook affecting credit standards for approving loans or credit lines to enterprises.
5. *Mortgages: Δ Standards*: Changes in credit standards for approving loans to households, loans for house purchase in the last three months.
6. *Mortgages: Costs-Funding*: Changes in the contribution of the following factors affecting credit standards for approving loans to households for house purchase, cost of funds and balance sheet constraints.

Concerning the ISTAT survey, the questionnaire can be found at [ISTAT questionnaire](#) (only in Italian). We refer to the following questions/answers:

- 43 Today, in our opinion, are the credit conditions more or less favorable compared to three months ago? (Possible answers: *More; Constant; Less*)
- 45 Have you obtained the loan you requested to the bank or financial institution? (Possible answers: *Yes, at the same conditions; Yes, at worse conditions; No; Only asking information*)
- 46 In case answer to 43 was *No* - Has the bank reject your request or you have not accepted their offer due to the conditions they were setting? (Possible answers: *The bank has not offered a loan; We have not accepted the loan due to not favorable conditions*)
- 47 In case answer to 45 was *Yes, at worse conditions* - Why the conditions have become worse? (Possible answers: *Higher rate; More personal collateral requested; More real collateral requested; Limits on the amount of the loan; Additional costs*)

D.2 High Frequency Variables

Table D.2: List of European and Italian events

Date	Events
2/7/07	HSBC issue with subprimes
6/7/07	Bearn Sterns first bad news
8/9/07	BNP Paribas
9/13/07	Northern Rock
2/18/08	Northern Rock Nationalized
3/14/08	Bearn Sterns bought by JP Morgan
9/15/08	Lehman
10/16/08	Greek Deficit Surprise
5/7/10	EFSF
7/23/10	Stress Test
10/28/10	ESM
5/17/11	Portugal asks help
8/5/11	Letter to Mr. Berlusconi from ECB
8/16/11	ECB buys after Ita take measures
10/4/11	Downgrade ITA-SPAIN
10/11/11	CDS-ban announced
10/31/11	Draghi takes over
11/1/11	CDS-ban in place
11/14/11	Mr. Monti takes over
12/5/11	Mr. Monti package
12/8/11	LTRO announced
12/21/11	1st LRTO
2/28/12	LTRO announced
6/26/12	Cyprus requests aid
7/26/12	Mr. Draghi whatever it takes
8/2/12	OMT announced
12/10/12	Monti resigns
12/13/12	SSM announced
11/7/13	ECB cuts Rate

Figure D.1: Italian BAS and Turnover on the MTS platform

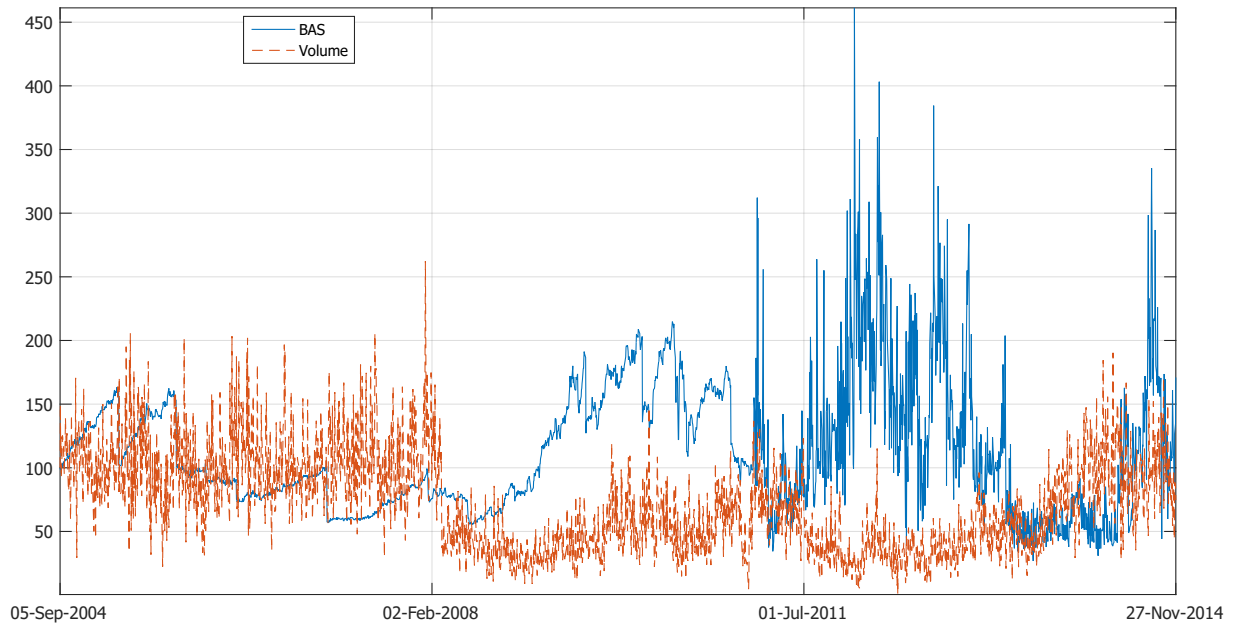
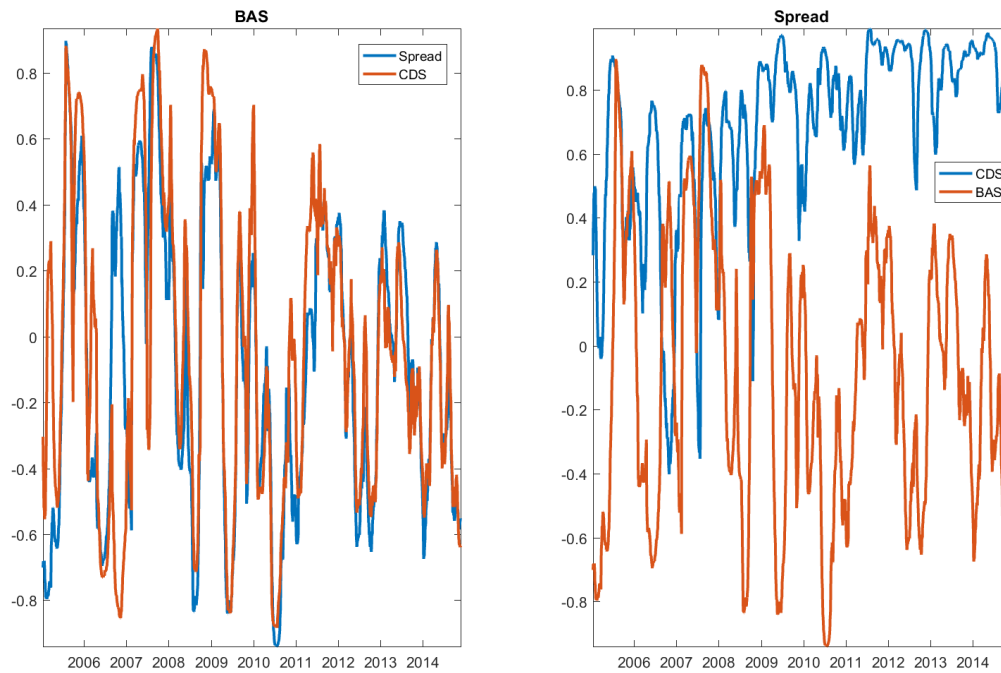


Figure D.2: Dynamic correlations among Spread, CDS and BAS over 2004-2014. Correlations are computed over a 90 days rolling window



D.3 Financial Variables at Monthly Frequency

Table D.3 summarizes statistics of the financial variables used in the empirical analysis at monthly frequency:

Table D.3: Descriptive statistics of sovereign debt financial variables at monthly frequency.

	Full Sample			2009-2014		
	BAS	Yield	CDS	BAS	Yield	CDS
Mean	0.017	4.318	98.278	0.020	4.41	169.58
Max	0.037	7.057	546.159	0.037	7.057	546.159
Min	0.007	1.990	2.343	0.007	1.990	36.352
St. Dev.	0.007	0.809	124.411	0.007	1.008	128.619
Auto Corr.	0.836	0.956	0.964	0.782	0.957	0.940

Sources: Bloomberg, Datastream and Bank of Italy. Maturities: BAS and CDS 2 years; Yield 10 years.

There is no significant change in volatility and standard deviation in the period of the sovereign debt crisis at monthly frequency.

D.4 Proxy-SVAR

We describe the the Proxy SVAR methodology that we use to identify the effects of BAS shocks and the first stage results (i.e. the linear projection of the reduced form residuals on the exogenous variations of BAS identified at daily frequency).

D.4.1 Theoretical Reference

Consider the following VAR:

$$Y_t = AY_{t-1} + u_t \quad (\text{D.1})$$

with Y_t a vector of endogenous variables and u_t is a vector of reduced form residuals with variance-covariance matrix Σ_u . The objective is to recover the structural form of the VAR, characterized by the vector of structural shocks $\varepsilon_t = B^{-1}u_t$:

$$Y_t = AY_{t-1} + B\varepsilon_t \quad (\text{D.2})$$

We can rewrite the VAR system as partitioned (or bivariate for a matter of interpretation):

$$\begin{bmatrix} Bas_t \\ X_t \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} Bas_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{bas} \\ \varepsilon_t^X \end{bmatrix} \quad (D.3)$$

The Proxy-SVAR is an identification strategy that (potentially) partially identifies the unknown B matrix. Namely, we aim at identifying only the block $\begin{bmatrix} B_{11} \\ B_{21} \end{bmatrix}$, which would allow us to compute the IRFs of the system to a structural innovation in the BAS. In order to reach the identification, we exploit information from outside the VAR system. We use the variable z_t as a proxy for the true structural shock ε_t^{bas} . z_t is assumed to be a proxy for (a component of) the true ε_t^{bas} with the following (instrumental variable) properties:

$$\begin{aligned} \mathbb{E} \left[\varepsilon_t^{bas} z_t \right] &\neq 0 \\ \mathbb{E} \left[\varepsilon_t^X z_t \right] &= 0 \end{aligned}$$

In fact, under those assumptions, we can obtain consistent estimates of $\begin{bmatrix} B_{11} \\ B_{21} \end{bmatrix}$ by taking an instrumental variable approach:

First Stage: regress $u_t^{bas} = \beta z_t + \xi_t$ obtaining \hat{u}_t^{bas}

Second Stage: $u_t^X = \frac{B_{21}}{B_{11}} \hat{u}_t^{bas} + \zeta_t$

Given that the BAS reacts one to one to its own structural shock (on impact), we can normalize $\frac{B_{21}}{B_{11}} = B_{21}$. The IRFs to a BAS shock can be then computed across different horizons as:

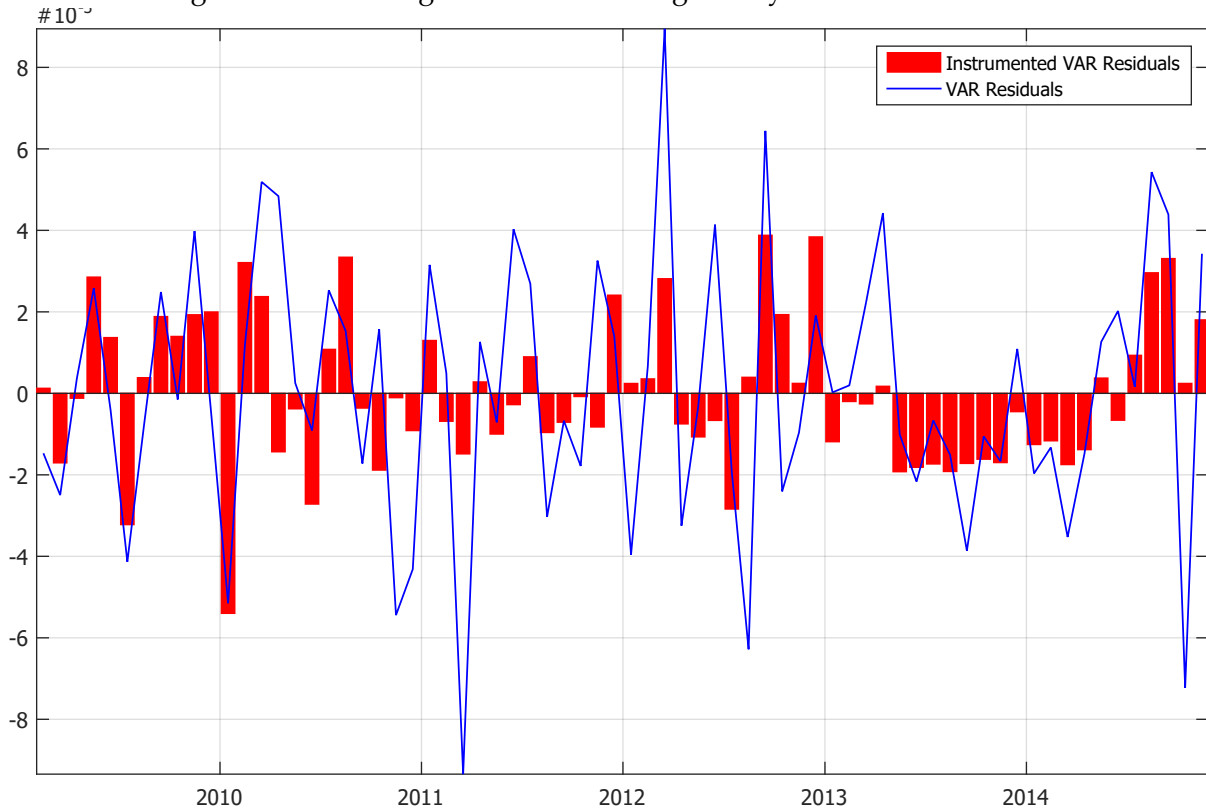
$$\mathcal{IRF}_0^X = B_{21}$$

$$\mathcal{IRF}_n^X = A^{n-1} \mathcal{IRF}_{n-1}^X \quad \forall n > 0$$

D.4.2 First Stage

Figure D.3 displays the RF residuals predicted by the proxy, compared to the original RF innovation series.

Figure D.3: First stage result of the Bridge Proxy-SVAR identification



Notes: The blue line represents the RF residuals of the BAS from the VAR featuring [Unemployment, π , Public Debt, R , $M2$, CC , BC , Financial Block]; the red bar is the RF residuals predicted by the Proxy (BAS shocks identified in a daily VAR including [BAS, CDS, Yield, FTSE, Eonia, VIX])

D.5 Alternative VAR Specifications

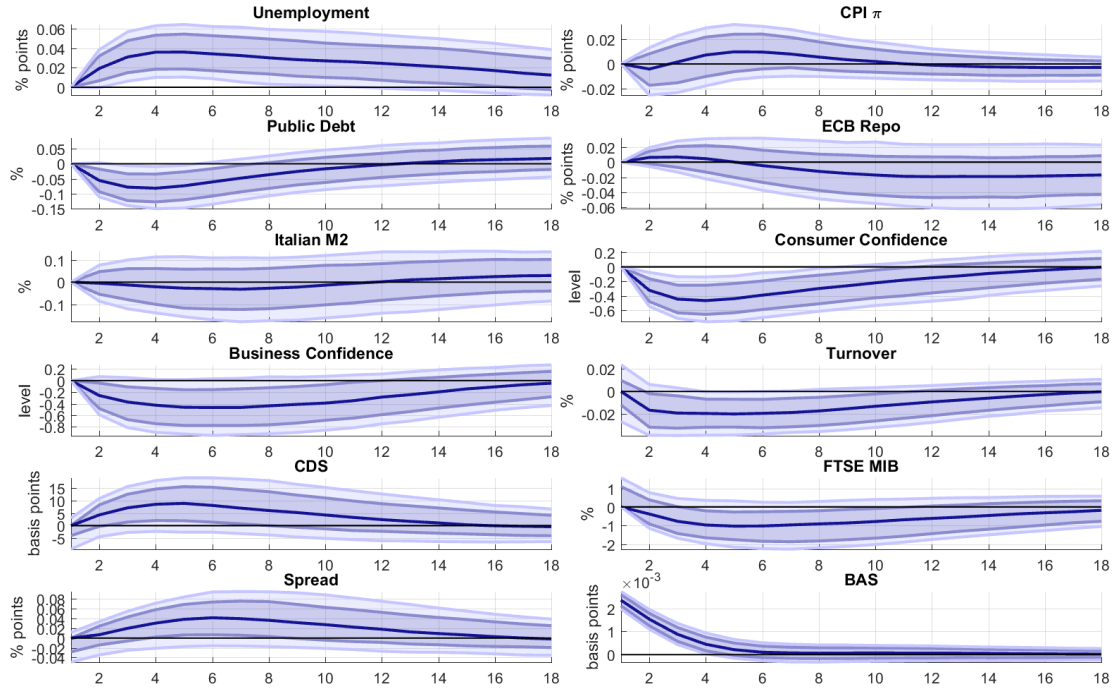
We present the results from alternative VAR specifications described in Section 4.3.4. To keep the appendix short, we only report results using some particular identification schemes (Basic, Full or Proxy SVAR). Results are robust using the other identification schemes and are available from the authors upon request.

D.5.1 Indicator of Liquidity

The following figures report the IRFs to a BAS shock of the Full VAR and Proxy-SVAR specifications including the Turnover instead of the Equity Premium, respectively. Moreover, we also display the IRFs and the FEVD of Unemployment from the Full VAR including

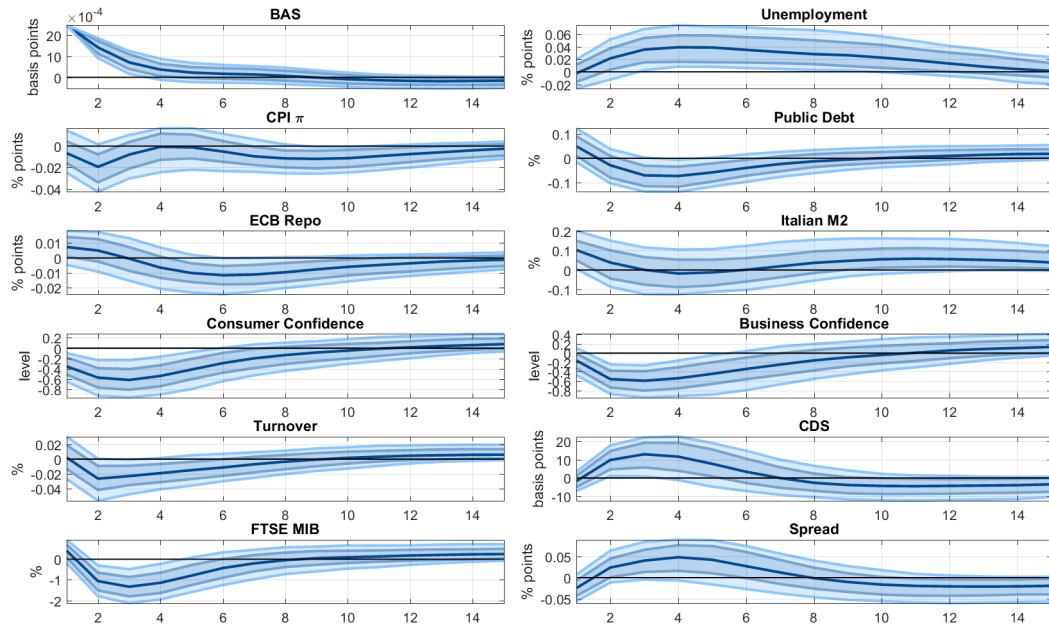
the Liquidity Index instead of the BAS. An increase (decrease) in the Liquidity Index is analogous to a decrease (increase) in the BAS.

Figure D.4: IRFs to a BAS Shock - Choleski identification



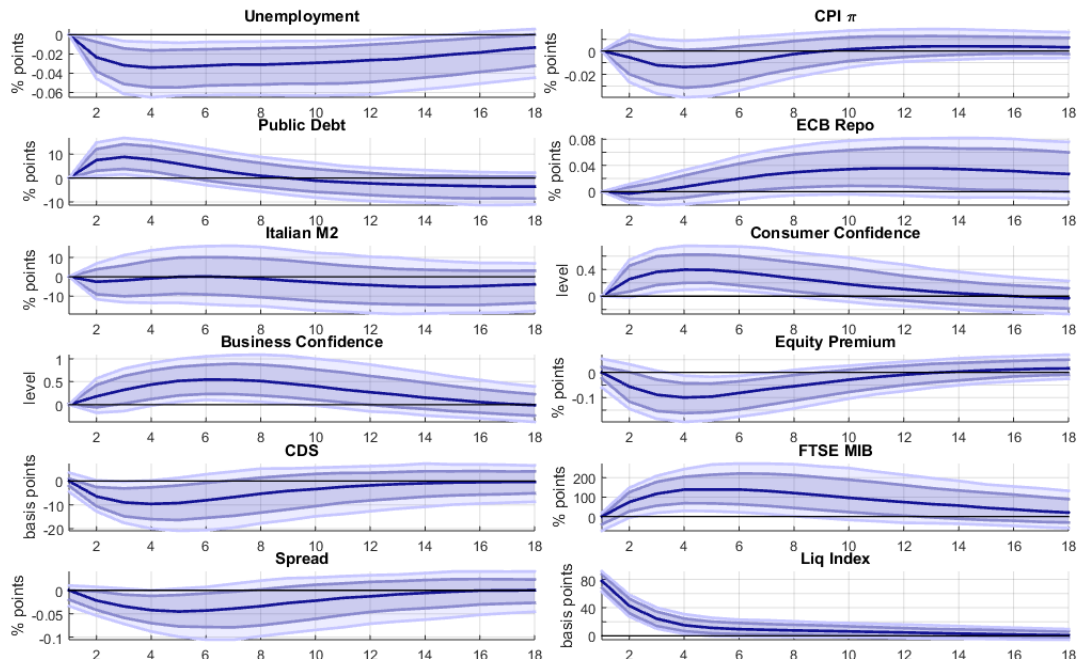
Notes: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The turnover of Italian sovereign bonds is included in place of the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block)

Figure D.5: IRFs to a BAS Shock - Bridge Proxy-SVAR identification



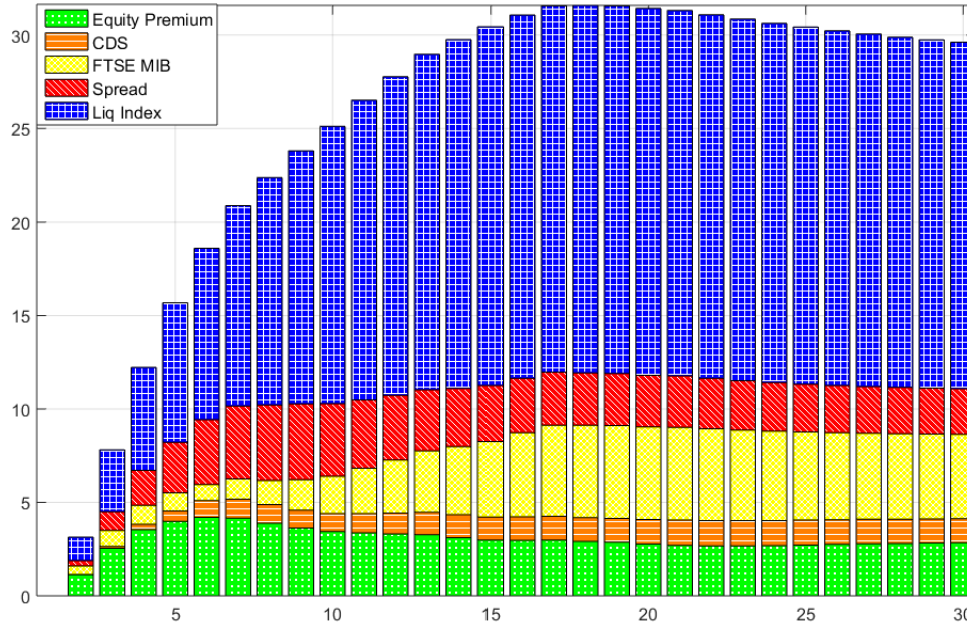
Notes: IRFs to a 1 standard deviation BAS shock in the VAR [IP, π , Public Debt, R, M2, CC, BC, Financial Block]. The turnover of Italian sovereign bonds is included in place of the equity premium. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

Figure D.6: IRFs to a Liquidity Index shock - Choleski identification



Notes: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure D.7: FEVD of unemployment - Choleski identification



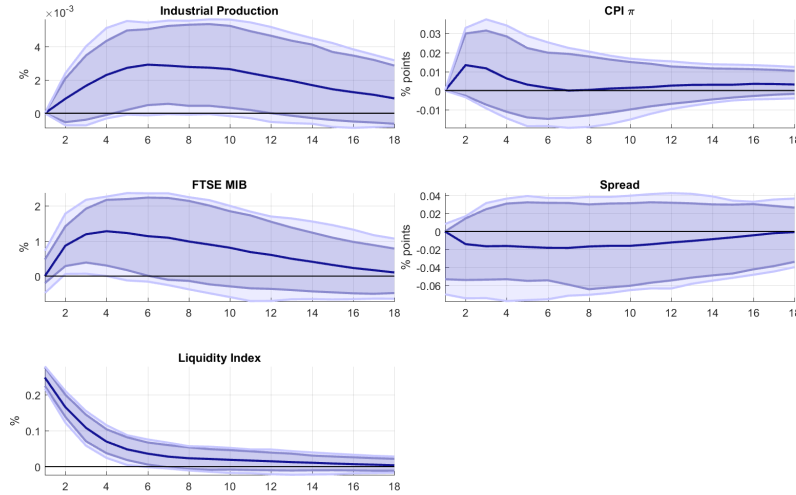
Notes: FEVD of unemployment including the Liquidity Index identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block].

Liquidity accounts for around 20% of Unemployment fluctuations in the period under analysis, in line with results presented in Section 4.3.2.

D.5.2 Measures of Economic Activity

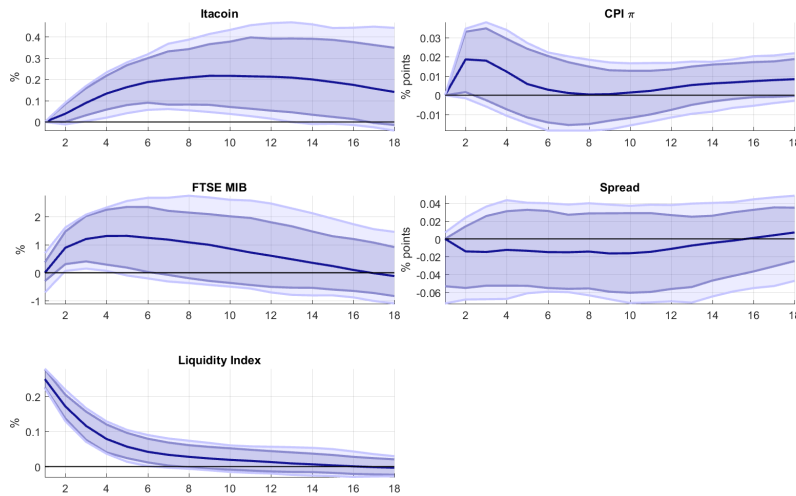
In this case, we use alternative measures of economic activity and present the corresponding IRFs. We include results both with our small VAR system and with the Proxy-SVAR. We employ Industrial Production and the ITA-Coin.

Figure D.8: IRFs to a Liquidity Index shock - Choleski identification and industrial production



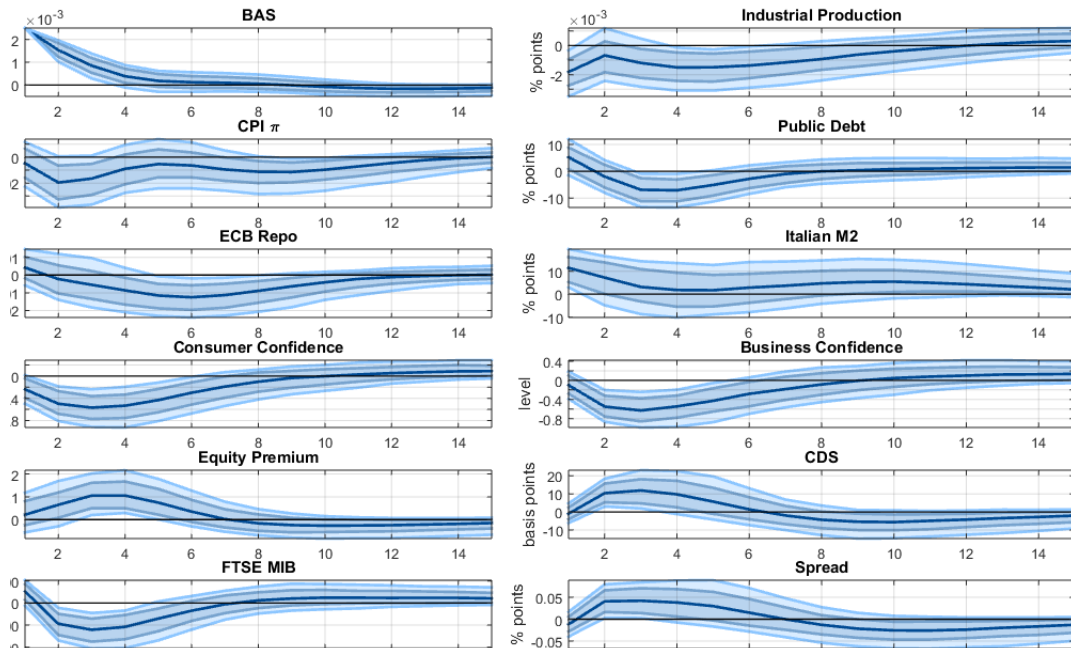
Notes: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Industrial Production, π , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure D.9: IRFs to a Liquidity Index shock - Choleski identification; Itacoin



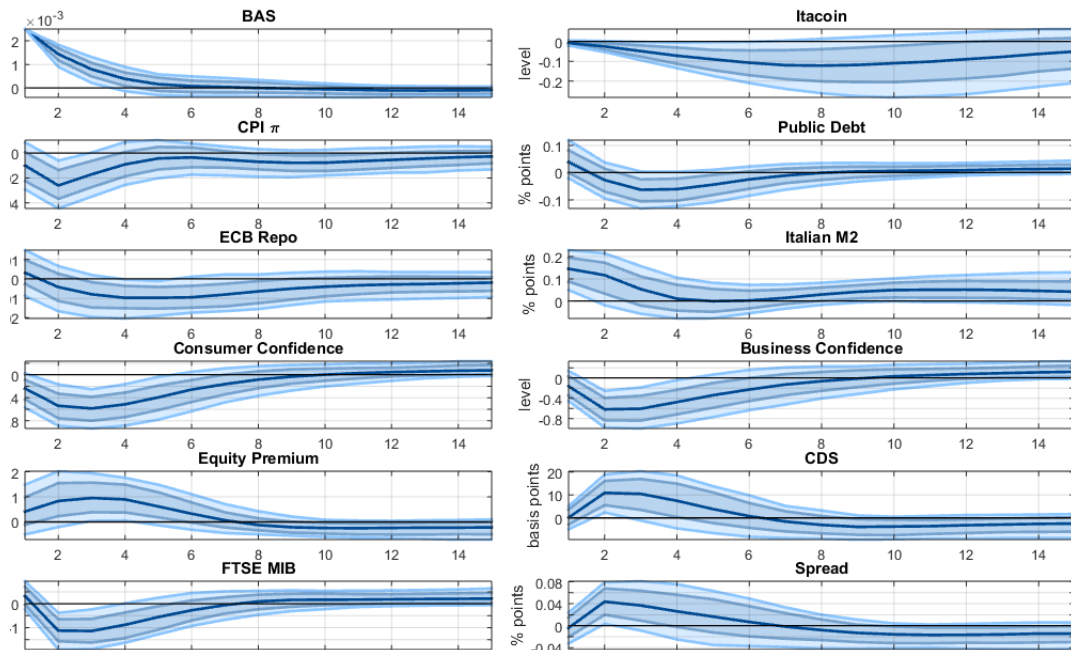
Notes: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Itacoin, π , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure D.10: IRFs to a BAS shock - Bridge Proxy-SVAR identification; industrial production



Notes: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [IP, π , Public Debt, R, M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Feb:2004-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

Figure D.11: IRFs to a BAS shock - Bridge Proxy-SVAR identification; Itacoin

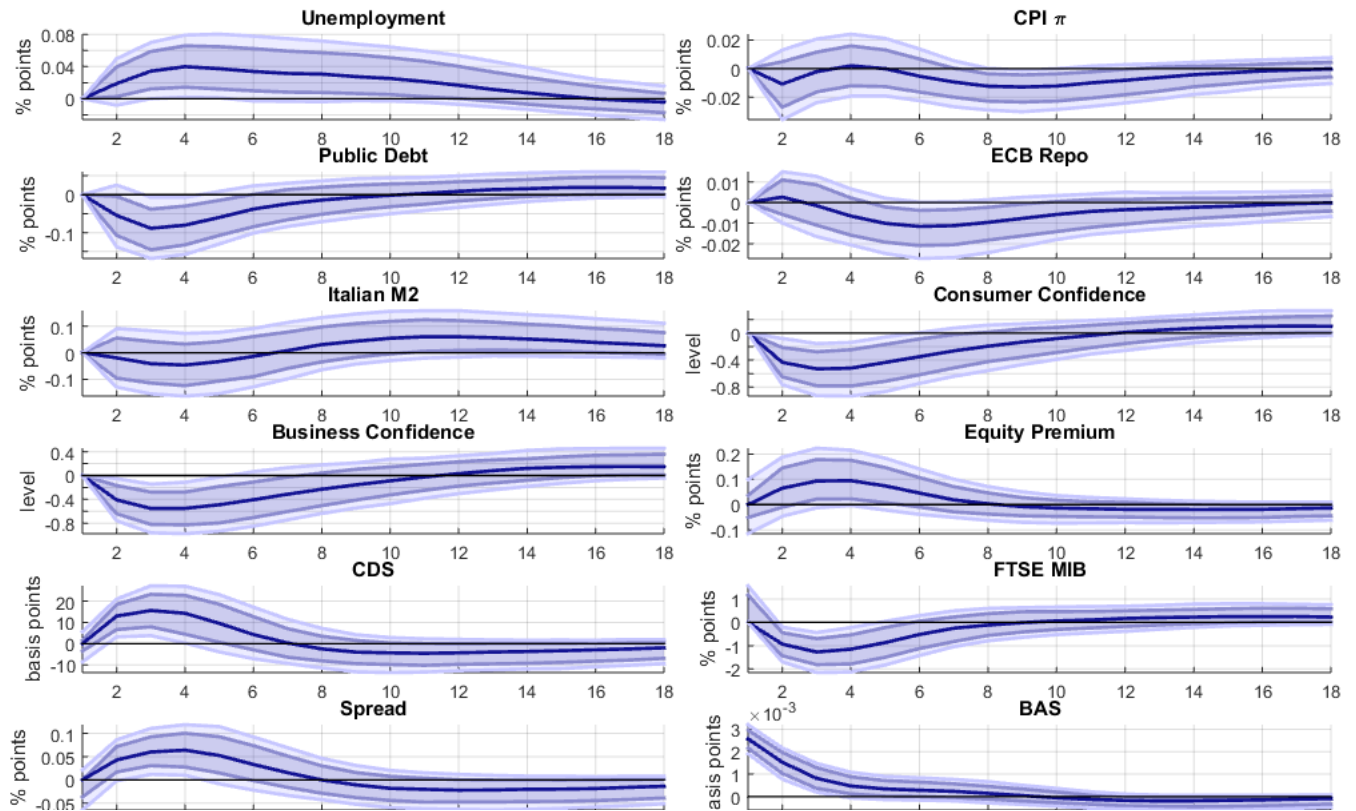


Notes: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [IP, π , Public Debt, R, M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Feb:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

D.5.3 Alternative Samples

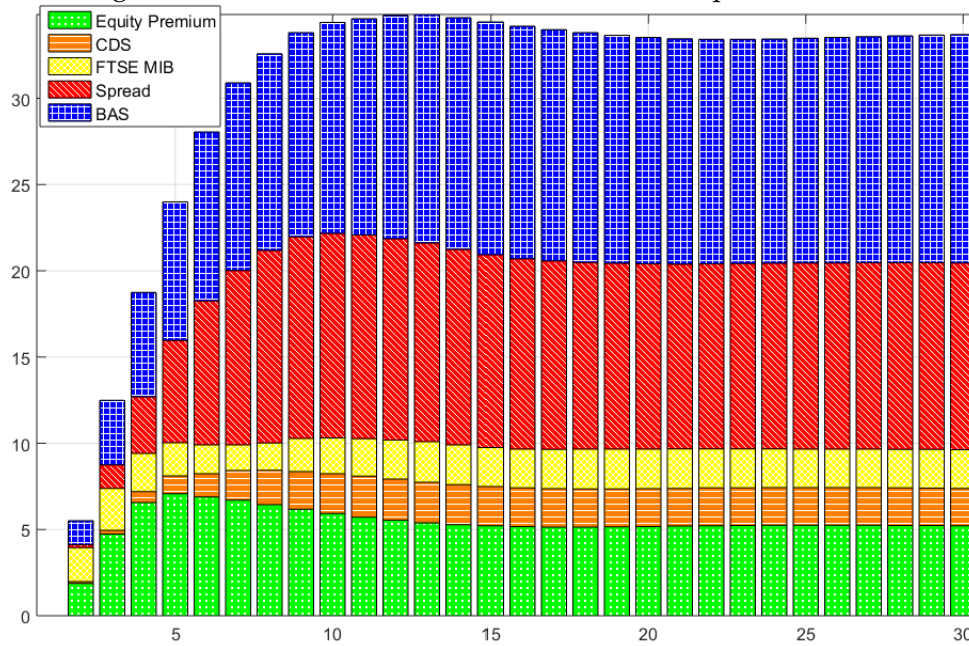
We study the dependence of our findings on the sample used. We display the IRFs to a BAS shock and FEV of Unemployment using the sample January 2009–November 2014 and on the pre-crisis sample (February 2004–December 2008). The main conclusions remain unchanged.

Figure D.12: IRFs to a BAS shock - Choleski; sample 2009–2014



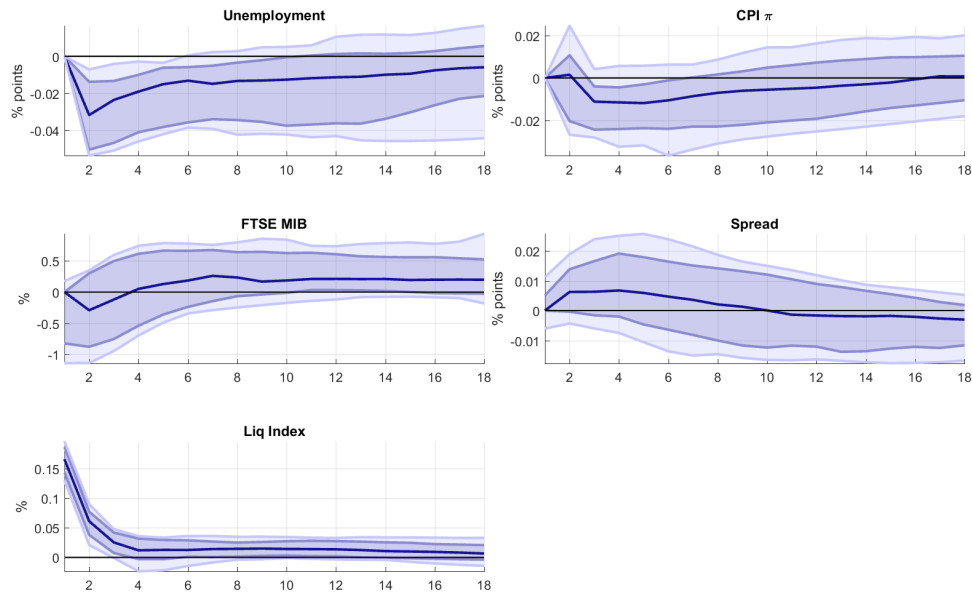
Notes: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure D.13: IRFs to a BAS shock - Choleski; sample 2009-2014



Notes: FEVD of unemployment including the Liquidity Index identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block].

Figure D.14: IRFs to a BAS shock - Choleski; sample 2004-2008



Notes: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment, π , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

D.5.4 Corporate Liquidity

In this section, we consider the relationship between the Corporate and Sovereign liquidity. Figure D.15 displays the evolution of the Corporate BAS together with sovereign variables aggregated at monthly frequency. Figure D.16 displays the IRF to a shock to corporate BAS and compares it to the one to a sovereign BAS. Finally, Figure D.17 shows the IRFs using as a variable the spread between Corporate and Sovereign BAS instead of the BAS.

Table D.4: Sovereign and Corporate Liquidity

Levels	BAS-S	Spread	CDS	BAS-C
BAS-S	1	-0.08	0.39*	0.31*
Spread	-0.08	1	0.35	0.5*
CDS	0.39*	0.35	1	0.9*
BAS-C	0.31*	0.5*	0.9*	1

Notes: Correlation over the 2004-2014 among Sovereign and Corporate BAS, Spread and CDS (as monthly averages).
Source of Corporate BAS: Bloomberg.

Figure D.15: Sovereign and Corporate BAS, Spread and CDS (as monthly averages)

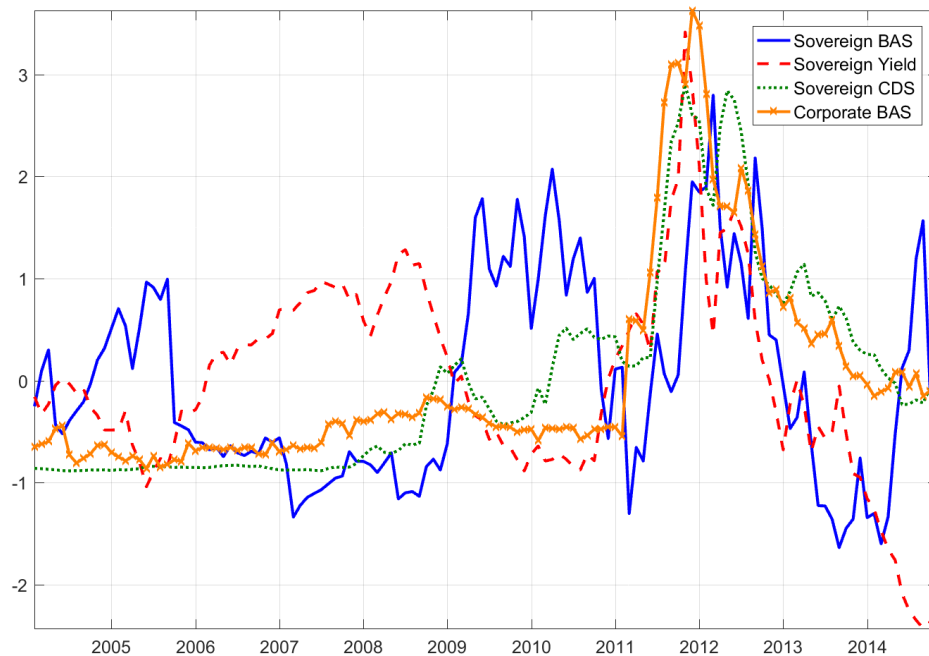
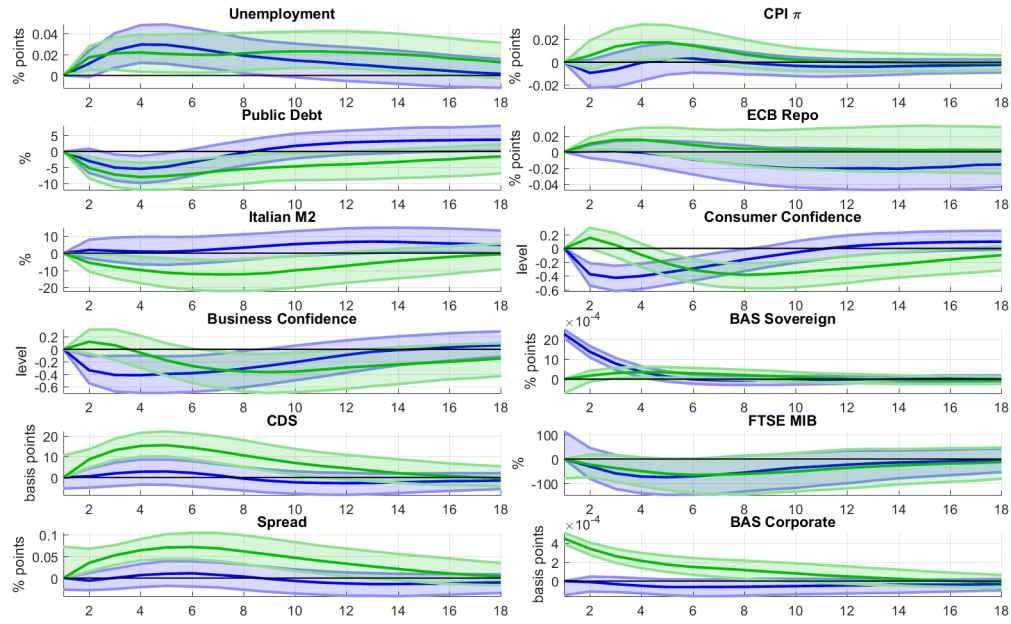
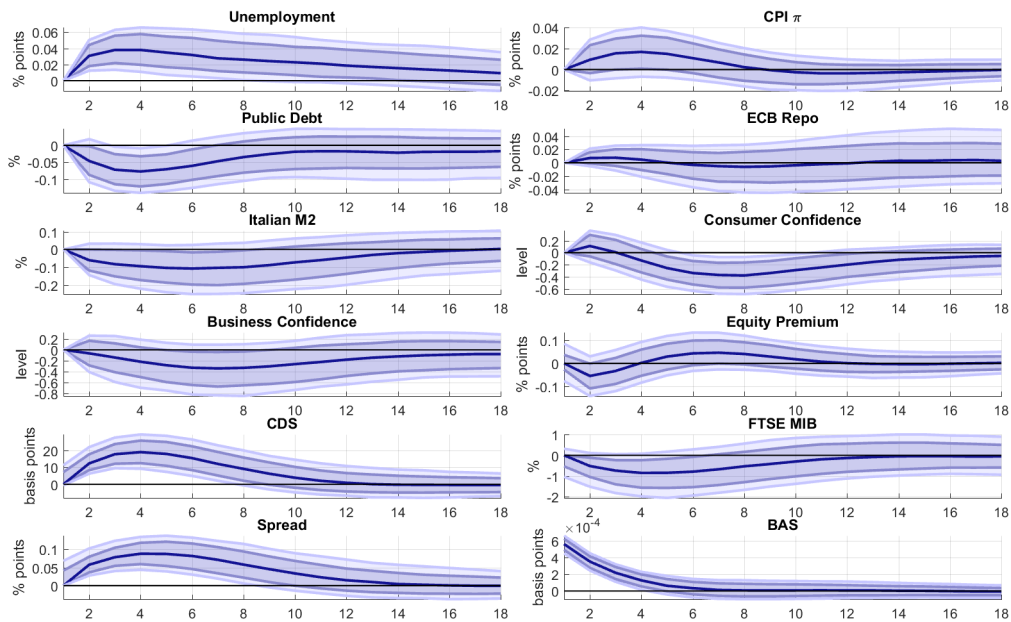


Figure D.16: IRFs to a BAS shock- Choleski identification; sovereign and corporate liquidity



Notes: IRFs to a 1 std Corporate BAS shock (compared to a sovereign BAS shock in blue) identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Figure D.17: IRFs to a BAS shock- Choleski identification; corporate bond liquidity

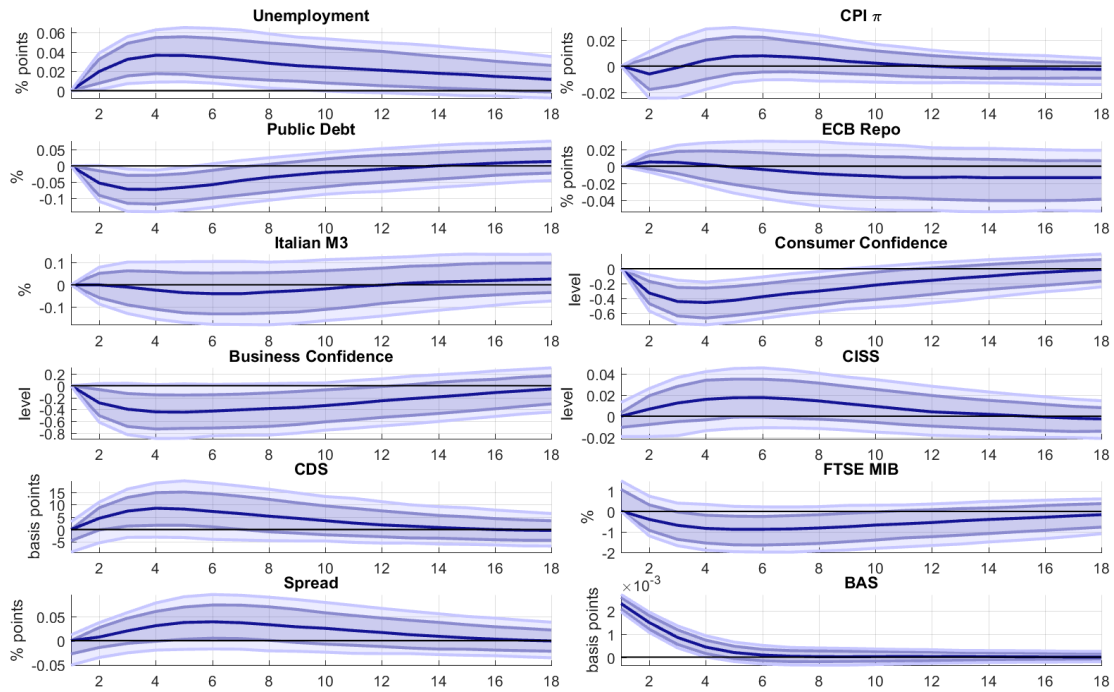


Notes: IRFs to a 1 std (Corporate-Sovereign) BAS shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

D.5.5 Market Stress Index

Figure D.18 displays the IRFs to a BAS shock of the enlarged VAR that includes the *Composite Indicator of Systemic Stress*, computed by the ECB.

Figure D.18: IRFs to a BAS shock- Choleski identification; CISS

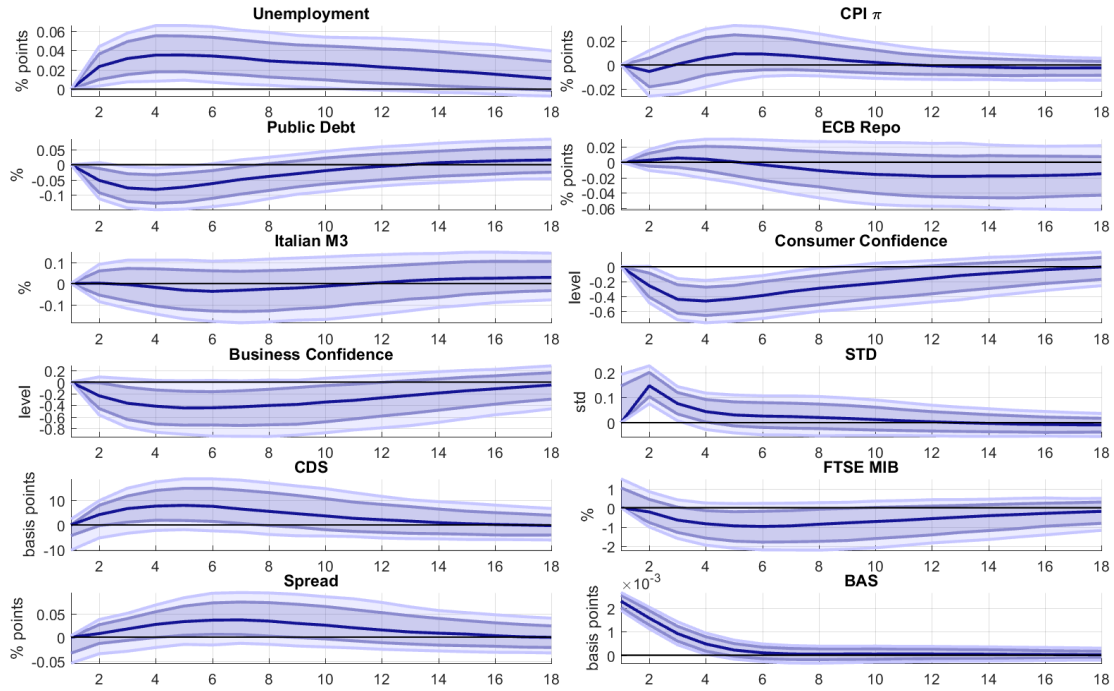


Notes: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. The CISS Index is included in place of the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

D.5.6 Financial Volatility

We report the IRFs to a BAS shock of the enlarged VAR that includes an indicator that account for volatility in sovereign debt markets. This indicator is defined as the first principal component of the realized monthly volatility of sovereign BAS, Spread and CDS, computed using daily data.

Figure D.19: IRFs to a BAS shock- Choleski identification; financial volatility



Notes: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment, π , Public Debt, R, M2, CC, BC, Financial Block]. A principal component that summarizes the volatility of financial variables is included in place of the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).