Financial frictions and global spillovers*

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Abstract

We investigate whether financial frictions facilitate the international propagation of financial shocks that originate from the United States. The US economy is modeled jointly with the G6 economies using a two-region threshold vector autoregression. This model captures regime-dependent dynamics conditional on the extent of financial frictions, gauged by a risk premium on US corporate bonds. Transition from a regime of unconstrained financial intermediation to one characterized by tight credit conditions arises whenever the bond risk premium exceeds a critical threshold. Our results reveal that, under binding credit constraints, rising US risk premia lead to a tightening of global financial conditions and to a decline in global trade, which trigger a significant worldwide output contraction.

JEL classification: C32; C34; E32; G01; F44

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1 Introduction

Frictions between lenders and borrowers wax and wane over the business cycle, thereby amplifying economic fluctuations. For instance, financial frictions arising from information asymmetries, incentive distortions, and collateral constraints transformed the 2007-08 financial crisis into the most severe recession worldwide since the Second World War. The crisis was triggered by losses on asset-backed securities, which raised investors' risk aversion due to fears about collateral values and counterparty risk. As a result, financial market liquidity dried up, leading to a credit crunch with pervasive consequences for the real economy. The turmoil in US financial markets sparked a systemic crisis that swept quickly across the globe. Yet there is only limited empirical evidence on the links between financial frictions and global spillovers. Against this backdrop, we investigate whether frictions in US financial markets facilitate the international propagation of financial shocks that originate from the US economy.

There is ample empirical evidence for an interplay between financial frictions and US business cycles. For example, Bernanke et al. (1996) show that economic downturns have a larger impact on borrowers who suffer from financial frictions due to high agency costs. Similarly, Meisenzahl (2014) finds that agency problems between borrowers and lenders constrain small businesses' access to credit, thereby stalling the recovery from the 2007-09 recession. Financial frictions are often embedded in macroeconomic models since the seminal work by Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Bernanke et al. (1999). Nevertheless, most empirical studies fail to capture the amplification and feedback loops implied by the theoretical literature, with the exception of Balke (2000), who employs a nonlinear threshold vector autoregression (TVAR) to study credit frictions in the US economy.

The 2007-08 financial crisis had a significant international dimension.[1] The rise in economic globalization observed since the mid-1980s offers some clues as to what may have contributed to this phenomenon.[2] For example, Krugman (2008) describes an "international finance multiplier" by which deteriorating economic conditions can be transmitted across borders through their effects on the balance sheets of internationally operating

[1]Among others, Longstaff (2010), Bems et al. (2011), Bagliano and Morana (2012), Cettorelli and Goldberg (2012), Eichengreen et al. (2012), Giannetti and Laeven (2012), De Haas and Van Horen (2013), and Kalemli-Ozcan et al. (2013) have shown that the recent crisis was transmitted across borders through international financial markets and the collapse of global trade.

[2]National economies underwent widespread integration since the mid-1980s, enabling trade and portfolio diversification across geographic regions. As a result, international financial integration has grown by a factor of seven (see Lane and Milesi-Ferretti, 2007). For instance, foreign investors' US corporate bond holdings increased nearly four-fold and so did also FDI inflows into the US, while US two-way trade has grown more than five-fold in nominal terms since the 1980s. Moreover, the international claims of global banks have grown ten-fold over the last three decades. For the main stylized facts see e.g. Kose et al. (2009) and Goldberg (2009).

financial institutions. If financial intermediaries are borrowing-constrained, a fall in asset values in one country can lead to balance sheet contraction in other countries, triggering a vicious cycle of balance sheet deterioration and asset fire-sales across countries. This deleveraging spiral results in a magnification of the initial shock and a synchronized worldwide decline in real economic activity. Comprehensive theoretical models that feature similar mechanisms have been developed by Devereux and Yetman (2010, 2011), Olivero (2010), Kollmann et al. (2011), and Dedola and Lombardo (2012). A handful of empirical studies, including Helbling et al. (2011) and Bagliano and Morana (2012), have recently assessed the effects of US financial shocks on the global economy. Nevertheless, the existing empirical literature does not explicitly model the nonlinear amplification mechanisms implied by financial frictions.

In this paper, we study international financial spillovers in the presence of frictions in US financial markets. The US economy is modeled jointly with the rest of the world (RoW) using a two-region structural TVAR. This model represents an empirical counterpart of the nonlinear DSGE models with occasionally binding credit constraints proposed by Mendoza (2010) and Bianchi and Mendoza (2010). Variation in the degree of financial frictions gives rise to nonlinear dynamics in our empirical model. Whenever financial frictions exceed a critical level, the economy shifts from a state characterized by unconstrained access to credit to one in which borrowers face stringent credit constraints. We gauge financial frictions by the degree of risk aversion in the US corporate bond market. The Excess Bond Premium (EBP) proposed by Gilchrist and Zakrajsek (2012) is used as a comprehensive proxy for risk aversion. The EBP measures a premium demanded by investors for bearing exposure to credit risk across the entire maturity spectrum (from 1- to 30-years) and the range of credit quality (from D to AAA) in the corporate bond market, beyond the compensation for the usual counter-cyclical movements in expected corporate default.[3] Gilchrist and Zakrajsek (2011) demonstrate in a DSGE framework that a rise in the EBP reflects a reduction in the risk-bearing capacity of the financial sector, which raises the cost of external finance and limits access to credit in the economy.

The US economy is strongly interconnected with the rest of the world via trade and financial linkages which constitute potential channels for the international transmission

[3] Gilchrist and Zakrajsek (2012) construct a composite credit spread index as an arithmetic average of credit spreads on senior unsecured corporate bonds issued by 1,112 nonfinancial firms. For each firm, the credit spread for a corporate bond of a given maturity is obtained as the difference between the corporate bond yield and the yield of a corresponding synthetic risk-free security from the Treasury yield curve. Gilchrist and Zakrajsek (2012) decompose the credit spread index using a Black-Scholes-Merton option-pricing model estimated under a risk-neutrality assumption. This model removes (i.) the systematic counter-cyclical movements in firm-specific distance-to-default, (ii.) the level, slope and curvature of the Treasury yield curve, and (iii.) the realized volatility of ten-year Treasury bonds. The EBP is the residual component unexplained by these factors, it thus reflects systematic deviations in the pricing of US corporate bonds relative to the expected default risk of the underlying issuers.

of shocks. To capture these channels, we add a range of variables to a baseline TVAR comprised of US output growth, US inflation, the federal funds rate, and the EBP, estimated on data spanning from January 1984 to December 2012. The variables considered include RoW output growth, realized stock market volatility, corporate bond spreads, short-term interest rates, nominal effective exchange rates, and the volume of US trade.

Our empirical results reveal an international dimension of the US financial accelerator mechanism. Although financial integration may in general enable economies to diversify their income portfolios across borders, it also comes at the price that shocks can spill over to other countries in times of crisis. In particular, regime-specific impulse response functions show that, when credit is abundant, financial shocks have a negligible effect on both the US and the global economy. On the contrary, under binding credit constraints, a rise in the US excess bond premium leads to a tightening of global financial conditions and to a decline in global trade which facilitate a significant worldwide output contraction.

The remainder of the paper is organized as follows. We present our econometric approach in section 2. Section 3 offers a brief description of the data, and it outlines our empirical results. Finally, section 4 summarizes our findings and concludes the paper.

2 Methodology

2.1 The threshold vector autoregressive model

Following Balke (2000), our point of departure is a 4-variate system for the US economy that comprises output growth (q_t), inflation (π_t), the federal funds rate (i_t), and a gauge of financial frictions (rp_t), proxied by the EBP obtained from Gilchrist and Zakrajsek (2012). $Y_t = (q_t,\ \pi_t,\ i_t,\ rp_t)$ is assumed to follow a threshold vector autoregression (TVAR) given in structural form by:

$$Y_t = \begin{cases} \mathrm{A}^1 Y_t + \Theta^1(L)Y_t + \varepsilon_t^1 & \text{if} \quad rp_{t-d} < \gamma, \\ \mathrm{A}^2 Y_t + \Theta^2(L)Y_t + \varepsilon_t^2 & \text{if} \quad rp_{t-d} \geq \gamma, \end{cases} \tag{1}$$

for $t \in \{1, ..., T\}$, where rp_{t-d} acts as a threshold variable with delay d. The parameter matrices A^1 and A^2 reflect the contemporaneous relationships between the endogenous variables contained in Y_t, while the lag polynomial matrices $\Theta^1(L) = \Theta_1^1 L^1 + ... + \Theta_{p_1}^1 L^{p_1}$ and $\Theta^2(L) = \Theta_1^2 L^1 + ... + \Theta_{p_2}^2 L^{p_2}$ describe their dynamic interaction. The vectors of orthogonal shocks ε_t^1 and ε_t^2 are normally distributed with zero mean and regime-dependent positive definite covariance matrices $\Sigma_\varepsilon^1 = E(\varepsilon_t^1 \varepsilon_t^{1\prime})$ and $\Sigma_\varepsilon^2 = E(\varepsilon_t^2 \varepsilon_t^{2\prime})$.

The TVAR postulates that, whenever the EBP crosses a threshold value γ, the economy shifts from a state of unconstrained financial intermediation ($rp_{t-d} < \gamma$) into one where borrowers face more stringent credit constraints ($rp_{t-d} \geq \gamma$). The VAR dynamics as well as the volatility of shocks may vary across these two regimes. Consequently, the EBP may amplify shocks hitting the economy. The parameters of the model are estimated using the maximum likelihood estimator (MLE) described in Galvao (2006); the estimation procedure is presented in Appendix A.

We estimate the threshold $\hat{\gamma}_{US}$ endogenously from the above described 4-variate TVAR model for the US economy. Subsequently, we augment Y_t with variables representing the rest of the world (RoW), and estimate the TVAR with $\hat{\gamma}_{US}$. This approach ensures that the identified financial regimes reflect distressed credit conditions in the US economy. We proxy RoW variables by weighted averages of six major industrialized economies (Canada, France, Germany, Italy, Japan, and the United Kingdom), following Helbling et al. (2011). We begin with a 6-variate TVAR with $Y_t = (q_t^*, q_t, \pi_t, i_t, rp_t, rp_t^*)$, where q_t^* represents RoW output growth and rp_t^* reflects financial conditions in the RoW, measured by realized stock market volatility in the G6. In order to capture different potential transmission mechanisms, a range of RoW variables are subsequently added one-by-one using a marginal approach. These include the short-term nominal interest rate, the nominal effective exchange rate, corporate bond spreads, and US trade with respect to the RoW.

2.2 Identification of US financial risk premium shocks

Conditional on the threshold γ, the TVAR model reduces to a piecewise linear VAR. Hence, we can obtain impulse responses which describe the dynamic effects of identified structural shocks *within* each regime, under the assumption that the economy resides in the same regime for the entire duration of the response (see e.g. Ehrmann et al., 2003; Candelon and Lieb, 2013). This approach yields regime-specific shocks recovered through a structural identification scheme.

Identification is achieved by imposing orthogonality restrictions on the contemporaneous relationships A^1 and A^2. In particular, the reduced form covariance matrices can be decomposed as $\Sigma_u^1 = (\mathrm{A}^1)^{-1}\Sigma_\varepsilon^1(\mathrm{A}^1)^{-1\prime}$ and $\Sigma_u^2 = (\mathrm{A}^2)^{-1}\Sigma_\varepsilon^2(\mathrm{A}^2)^{-1\prime}$, from which orthogonal regime-specific shocks can be recovered as $\varepsilon_t^1 = \mathrm{A}^1 u_t^1$ and $\varepsilon_t^2 = \mathrm{A}^2 u_t^2$. We attach an economic interpretation solely to the US risk premium shock, while we do not interpret the remaining orthogonal shocks from a structural perspective (i.e., these may reflect a mixture of the true underlying structural disturbances).

The US risk premium shock is recovered by a Cholesky decomposition of the regime-specific reduced-form covariance matrices Σ_u^1 and Σ_u^2, whith the following recursive ordering of the shock vector: $\varepsilon_t^s = [\varepsilon_{q^*,t}^s, \varepsilon_{q,t}^s, \varepsilon_{\pi,t}^s, \varepsilon_{i,t}^s, \varepsilon_{rp,t}^s, \varepsilon_{rp^*,t}^s]$, where $s = 1, 2$. Thus, our identifying assumption entails that risk aversion in the US financial sector responds without delay to all macroeconomic and policy shocks hitting the global economy, while the macro-economy reacts with a slack to financial shocks. Our recursive identification scheme thus acknowledges the high-frequency nature of financial markets, which constitutes a standard approach in the VAR literature (see also Thorbecke, 2009; Bjornland and Leitemo, 2009; Gilchrist and Zakrajsek, 2012).[4]

3 Empirical results

3.1 Data

We use monthly data between January 1984 and December 2012. Hence, our sample ranges from the ascent of the Great Moderation until the recent post-crisis recovery, and it covers a period of rapid international trade and financial integration. We proxy output by industrial production series and we measure inflation as the growth rate of consumer prices. Time series for the US are obtained from the Federal Reserve Bank of St. Louis and from Gilchrist and Zakrajsek (2012).[5]

RoW variables are proxied by weighted averages of time series for Canada, France, Germany, Italy, Japan, and the United Kingdom. The weights reflect the average overall size of the economy over the estimation period, and they are based on PPP-adjusted annual real GDP from the Penn World Tables. We use industrial production data for the G6 obtained from the OECD. Monthly realized stock market volatility is obtained as the sum of squared daily stock market returns within the month. We use the MSCI price index of the total national stock market, retrieved from Datastream. For each country, the nominal monetary policy rate is used. In addition, we consider the nominal effective exchange rate index of the US with respect to its 15 main trading partners reported by the Bank for International Settlements. We use the spread between long-term corporate and government bonds from the IMF Stress Index data set. Finally, we proxy US trade by the total sum of bilateral imports and exports between the US and the G6 (deflated by US CPI), obtained from the IMF Direction of Trade statistics.

[4]The Wold-causal order between financial conditions in the US and the RoW is somewhat ambiguous. In the benchmark model, we allow for a contemporaneous reaction of global financial conditions in response to US financial shocks. However, our central findings are robust to reversing the order, as we shall see in a robustness exercise.

[5]The data of Gilchrist and Zakrajsek (2012) was retrieved from the *American Economic Association* webpage at: http://www.aeaweb.org/articles.php?doi=10.1257/aer.102.4.1692, and we are grateful to Simon Gilchrist and Egon Zakrajsek for kindly supplying the extended time series that span until December 2012.

Table 1: Model selection criteria

Selection criterion	q_t^*	q_t	π_t	i_t	rp_t	rp_t^*
US Model						
BW		4.18	4.02	4.87	4.39	
BLM		3.88	3.75	4.42	4.05	
Spillover Model						
BW	4.32	5.18	4.10	5.52	5.49	5.63
BLM	3.99	4.64	3.82	4.88	4.86	4.96

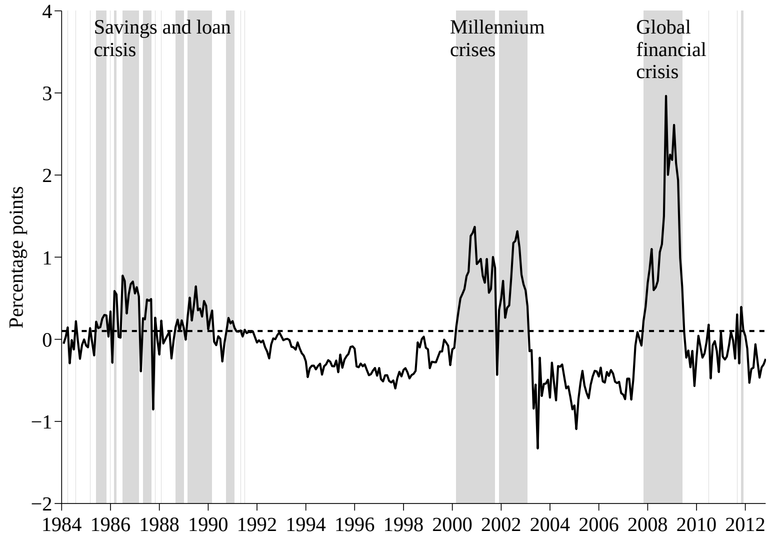
Note: The table shows the BW and BLM statistics for each equation of the estimated models. The nonlinear TVAR model is chosen over the linear VAR if BW > 1 and, similarly, if BLM > 1.

3.2 Model selection

We employ three statistics in order to choose between a linear and a threshold VAR model (the analytical details are presented in Appendix B). First, we test the null hypothesis of a constant-parameter linear VAR model against the threshold-VAR alternative using the heteroskedasticity-robust SupLM statistic proposed by Hansen and Seo (2002). The threshold γ is not identified and constitutes a nuisance parameter under the null. Hence, the asymptotic distribution of the test statistic must be approximated via a bootstrap simulation method (see Hansen, 1996). We obtain a SupLM value of 126.457 (p-value=0.042) which implies a rejection of the null hypothesis of linearity in favor of the TVAR alternative. Rejection of the null suggests that financial frictions give rise to significant nonlinearities.

In addition, following Altissimo and Corradi (2002), Galvao (2006), and Artis et al. (2007), we use the bounded supWald (BW) and bounded supLM (BLM) statistics, which constitute consistent model selection criteria when a nuisance parameter is present only under the nonlinear alternative. The TVAR model is preferred over the linear VAR if the statistics exceed unity (BW $>$ 1 and, similarly, BLM $>$ 1). This model selection rule ensures that type I and type II errors are asymptotically zero. Table 1 shows the BW and BLM statistics that guide our model selection between a constant-parameter linear VAR against the threshold-VAR alternative. The table shows the test statistics for each individual equation in the baseline 4-variate US model and in the 6-variate spillover model. Again, the equation-wise supremum statistics speak unequivocally in favor of the nonlinear model.

Figure 1: Excess bond premium and financial regimes



Note: The solid line depicts the lagged excess bond premium and the dashed line corresponds to the estimated threshold value ($\hat{\gamma} = 0.1004$). Risk-averse periods are shaded in grey. Sample: January 1984 - December 2012.

3.3 Financial regimes

We estimate a 4-variate TVAR model comprising US output growth, inflation, the fed funds rate and the EBP with $p_1 = 4$ and $p_2 = 6$ lags selected using the Akaike information criterion (AIC) proposed by Tsay (1998) and the bias-corrected AIC proposed by Wong and Li (1998). The estimated threshold value equals $\hat{\gamma} = 0.1004$ percentage points with a delay of $\hat{d} = 1$ month. The fact that $\hat{\gamma}$ is close to zero lends a natural interpretation to the identified regimes in terms of risk tolerance (negative values of EBP) vs. risk aversion (positive EBP).

Figure 1 illustrates the lagged EBP (solid line) together with the estimated threshold (dashed line). The shaded areas correspond to periods when the EBP resides above the threshold. At a first glance, three major episodes of distress in US banking and credit markets stand out. The first wave of tight credit coincides with a series of savings and loan crises during the 1980s and early 1990s. An exhaustive historical account of the banking crises of that era is presented in Federal Deposit Insurance Corporation (1997). Following a period of financial prosperity during the 1990s, the US economy was again characterized by stringent credit supply conditions at the wake of the new millennium, around the Enron, Y2K, and 9/11 debacles, and the burst of the dotcom bubble. Finally, credit constraints were binding throughout the global financial crisis dated by the TVAR from December 2007 till July 2009.

3.4 Structural analysis

In this section, we trace the effects of a US financial risk premium shock on the global economy in the presence of financial frictions. To capture potential asymmetries across regimes, we calculate regime-specific structural impulse response functions (IRFs).[6] Figure 2 depicts IRFs to a one-percentage-point rise in the EBP from the 6-variate TVAR model over 48 months (the IRFs from the 4-variate model are nearly identical).[7] The solid lines represent the IRFs from a linear VAR model (without financial frictions), with bootstrapped 90% confidence bands shaded in grey. Blue diamonds (red dotted lines) represent the regime-specific IRFs from the TVAR model in the unconstrained (constrained) credit regime, with dashed-dotted (dashed) lines representing 90% confidence bands.

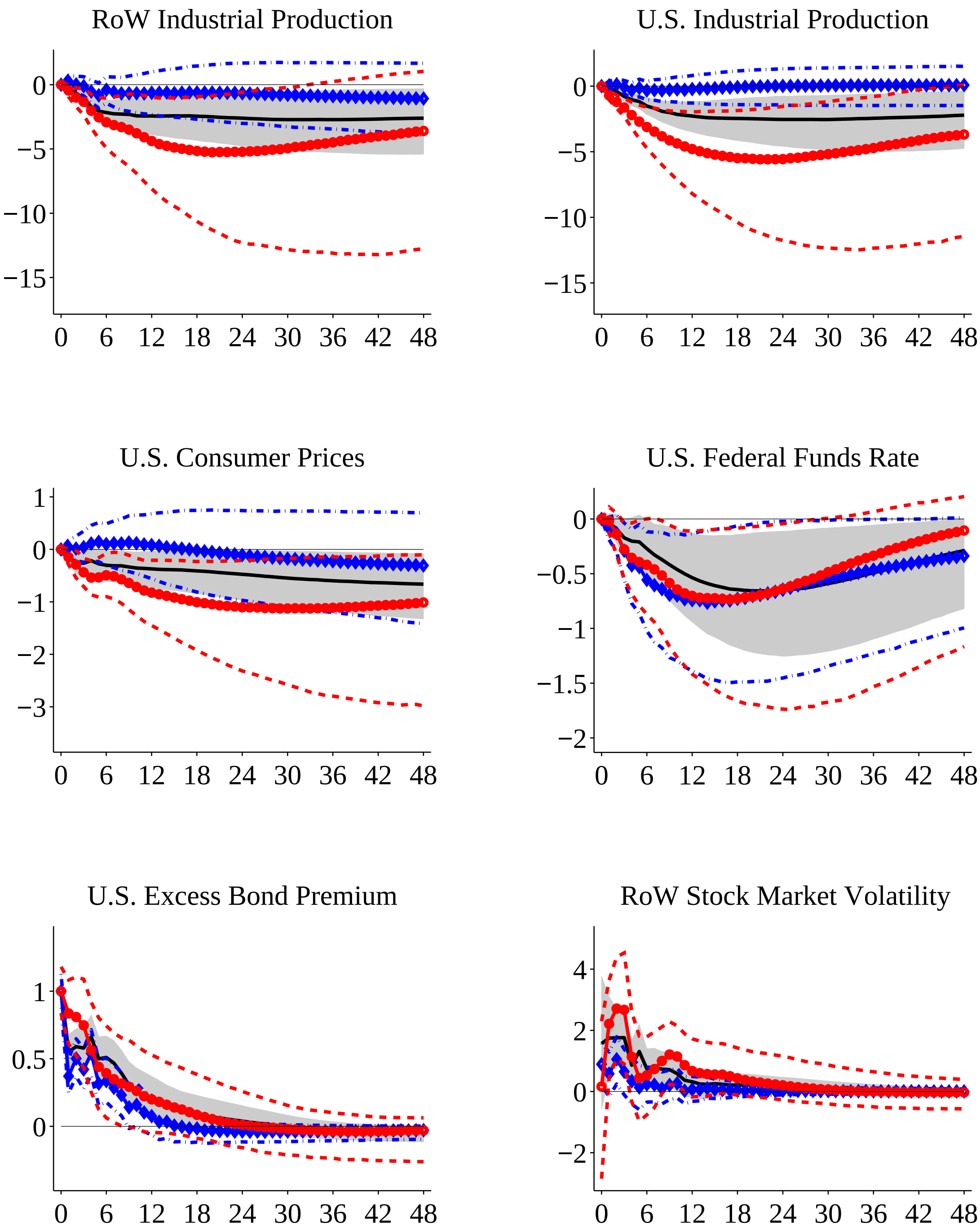
A US financial shock amounts to a rise in risk aversion that dies out after 9 months in both regimes. The federal funds rate falls by about 75 basis points within a year after the shock, which suggests that monetary policy takes an accommodative stance in the face of tightening financial conditions. Upon distinguishing between periods of unconstrained vs. constrained access to credit, we find a strong asymmetry in the strength of the macroeconomic responses across regimes. The EBP shock does not propagate beyond the US financial system when credit is abundantly available. On the contrary, the financial shock is detrimental for the real economy under stringent credit conditions, leading to a significant decline of industrial production and consumer prices. This suggests that firms and households postpone investment and consumption plans when faced with binding credit constraints. Remarkably, the associated US recession generates worldwide repercussions due to financial links with the rest of the world. A rise in the EBP triggers a strong increase in global financial uncertainty (proxied by RoW stock market volatility), which facilitates a significant international output contraction. Deteriorating global financial conditions serve as a conduit for the US financial shock, in the spirit of an international finance multiplier described by Krugman (2008), Devereux and Yetman (2010, 2011), Olivero (2010), Kollmann et al. (2011), and Dedola and Lombardo (2012).

To study the international propagation of EBP shocks, we augment the TVAR with a range of RoW variables one-at-a-time. Figure 3 depicts IRFs of these additional variables (we omit plotting all IRFs from the TVAR, as they are largely robust to variations of the model). Our results suggest that global trade and corporate bond markets serve as additional (real and financial) transmission channels through which US financial shocks spill over to the rest of the world. In the tight credit regime, US trade contracts significantly

[6]The regime-dependent IRF amounts to a linear IRF conditional on a given regime (see e.g. Ehrmann et al., 2003; Candelon and Lieb, 2013). This approach yields regime-specific shocks uncovered through a structural identification scheme, which constitutes an advantage compared to the generalized IRFs occasionally used in the literature.

[7]The 6-variate model is estimated with $p_1 = 3$ and $p_2 = 6$ lags, to have a parsimonious model.

Figure 2: US financial shocks in the spillover model



Note: Impulse responses to a one-percentage-point rise in the EBP over 48 months in the 6-variate spillover model. The impulse responses of output growth and inflation were accumulated. The solid lines are the IRFs from the linear VAR model with shaded areas representing bootstrapped 90% confidence bands based on 2000 draws. The blue diamonds are the IRFs from the TVAR model in the unconstrained credit regime with dashed-dotted lines representing 90% confidence bands. The red dotted lines are the IRFs from the TVAR model in the tight credit regime with dashed lines representing 90% confidence bands.

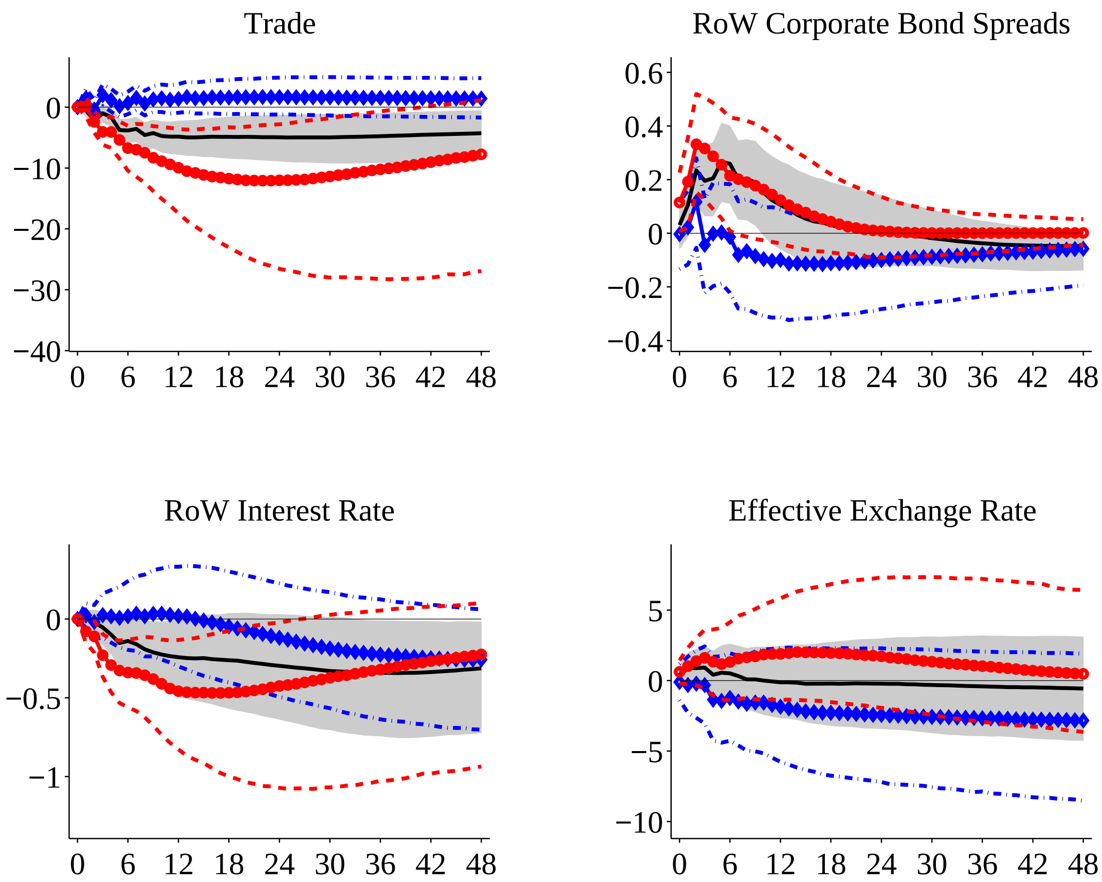
for more than 3 years after the financial shock, while there is no significant response in the unconstrained credit regime. Similarly, when US financial markets are in turmoil, global corporate bond spreads rise significantly following a rise in the US risk premium. This tightening of global financial conditions is accompanied by a worldwide monetary expansion, amounting to a 50 basis point decline in the global short-term interest rate. In contrast global interest rates and spreads do not respond significantly to US financial shocks in periods when the US financial system is in good health. The nominal effective exchange rate appreciates in the constrained credit regime, while it depreciates in the unconstrained regime. Even though the exchange rate responses are not significant, they are largely in line with the recent literature on US dollar exchange rate movements. For instance, Fratzscher (2009) documents a sharp appreciation of the US dollar against all currencies during the global financial crisis. The lion's share of this appreciation can be attributed to US-specific shocks and a flight-to-safety phenomenon by investors, also termed "the dollar trap" by Prasad (2014).

We postulate that there may be an international portfolio diversification motive behind the declining tendency of foreign exchange rates and corporate bond spreads during non-crisis periods. In particular, a rise in the EBP together with an insignificant response of global financial volatility in "normal" times implies that US financial assets become relatively more risky. Hence, investors may diversify their portfolios away from US markets, driving up the demand for foreign assets, which would lead to a decline in corporate spreads and a US dollar depreciation, in lnie with the patterns observed here. In sum, these findings draw attention to the advantages and pitfalls of global financial integration. Financial globalization is generally beneficial, as it enables countries to specialize their production in industries in which they have a comparative advantage and at the same time diversify their very risky income portfolios (see e.g. Rogoff, 1999). Nevertheless, financial interdependence comes at the price that shocks are easily transmitted across borders (see e.g. Beine et al., 2010; Longstaff, 2010; Bagliano and Morana, 2012; Cettorelli and Goldberg, 2012; De Haas and Van Horen, 2013).

We verify the robustness of our findings against variations of the baseline model specification. First, we reverse the order of the EBP and RoW stock market volatility. Second, two alternative weighting scheme of G6 variables are considered, based on bilateral financial positions and bilateral trade. The first column of Figure 4 depicts the IRFs to a rise in the EBP with RoW stock market volatility ordered above the EBP. The second and third columns of Figure 4 show the IRFs from the models with financial and trade weights, respectively.

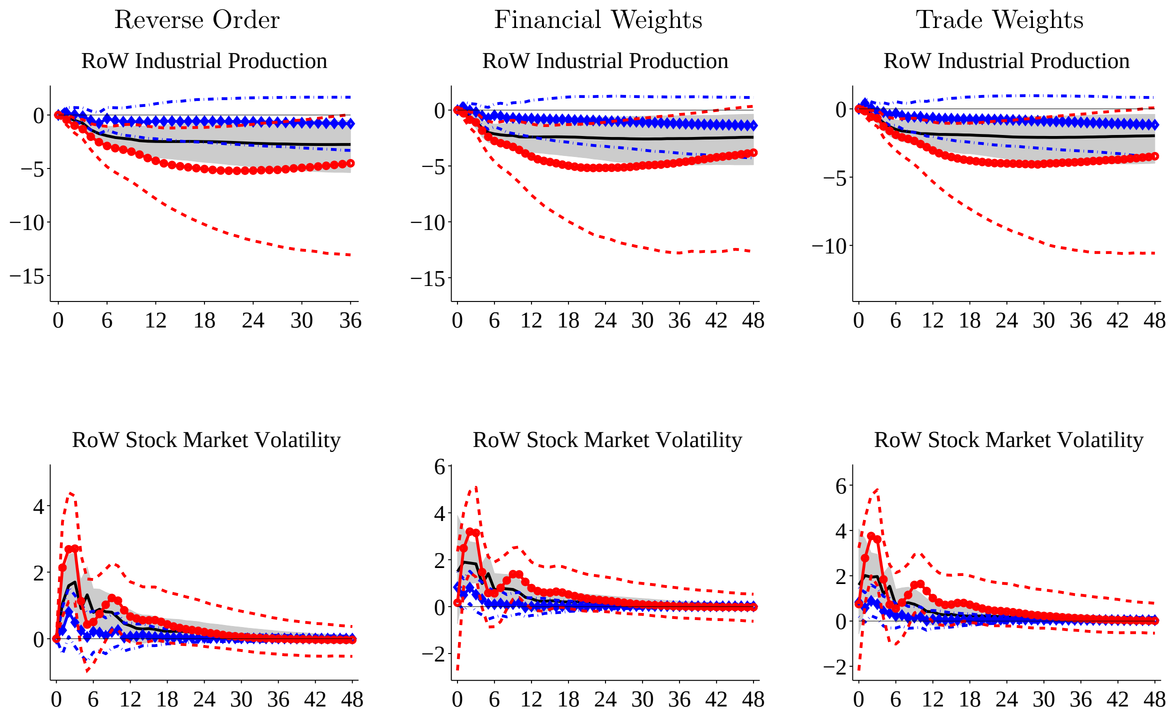
Following Imbs (2004), financial weights are constructed as $w_i^{Fin} = |(NFA_i/GDP_i) - (NFA_{US}/GDP_{US})$, using the data from Lane and Milesi-Ferretti (2007). NFA_i denotes

Figure 3: Transmission channels



Note: Impulse responses to a one-percentage-point rise in the EBP over 48 months in a 7-variate spillover model. The impulse responses of output growth and inflation were accumulated. The solid lines are the IRFs from the linear VAR model with shaded areas representing bootstrapped 90% confidence bands based on 5000 draws. The blue diamonds are the IRFs from the TVAR model in the unconstrained credit regime with dashed-dotted lines representing 90% confidence bands. The red dotted lines are the IRFs from the TVAR model in the tight credit regime with dashed lines representing 90% confidence bands.

Figure 4: Robustness checks



Note: Impulse responses to a one-percentage-point rise in the EBP over 48 months in a 7-variate spillover model. The impulse responses of output growth and inflation were accumulated. The solid lines are the IRFs from the linear VAR model with shaded areas representing bootstrapped 90% confidence bands based on 5000 draws. The blue diamonds are the IRFs from the TVAR model in the unconstrained credit regime with dashed-dotted lines representing 90% confidence bands. The red dotted lines are the IRFs from the TVAR model in the tight credit regime with dashed lines representing 90% confidence bands.

the net foreign asset position in country i. The weight w_i^{Fin} will take high values for countries that have diverging external positions with respect to the US, as such countries are more likely to lend and borrow from the US according to Imbs (2004). Following Frankel and Rose (1998), trade weights are constructed as $w_i^{Tra} = (EX^{\text{US to } i} + IM^{\text{US from } i})/(\sum_i EX^{\text{US to } i} + \sum_i IM^{\text{US from } i})$, where $EX^{\text{US to } i}$ denotes US exports to country i and $IM^{\text{US from } i}$ denotes US imports from country i. The financial as well as the trade weights are normalized and sum to 1.

In summary, our main findings remain unchanged in that an unexpected rise in US risk premia triggers a rise in global financial volatility and a contraction of international industrial production in periods when financial constraints are binding. Meanwhile, the responses are subdued and predominantly insignificant in periods when borrowing is relatively cheap in US financial markets. This asymmetry prevails across all model specifications.

4 Conclusion

Even though financial frictions are often embedded in structural macroeconomic models, most empirical studies on macro-financial linkages resort to linear models that do not account for the amplification mechanisms implied by the theoretical literature. There is an equally limited empirical literature that investigates the relation between financial frictions and global spillovers. This paper aims to fill these gaps. We show that financial frictions amplify business cycle fluctuations within as well as across economies.

We model economic activity in the US jointly with the G6 economies using a threshold vector autoregressive model. This model captures regime-dependent dynamics in the presence of financial frictions. Transition from a state of unconstrained financial intermediation to a regime characterized by binding financial constraints arises endogenously in this framework. We capture US financial frictions by an excess bond risk premium proposed by Gilchrist and Zakrajsek (2012). This premium reflects systematic deviations in the pricing of US corporate bonds relative to the expected default risk of the underlying issuers, it thus provides a useful gauge of credit supply conditions in the US economy.

Using the excess bond premium as a threshold variable, we identify three prolonged periods of distress in US banking and credit markets. The first tight credit episode coincides with the savings and loan banking crises of the 1980s and early 1990s. The US economy was also characterized by tight credit market conditions in the early 2000s, around the Enron, Y2K, and 9/11 debacles and following the burst of the dotcom bubble. Finally, the 2007-09 crisis is identified as the most recent credit crunch.

We trace the effects of US financial disturbances on the global economy through regime-specific impulse response functions. Upon distinguishing between normal and tight credit regimes, we uncover a strong asymmetry in the strength of the responses. The US financial sector absorbs the risk premium shock when borrowers have unconstrained access to credit, and there are no aggregate economic consequences. In contrast, an unexpected rise in the US risk premium triggers a significant contraction in the global economy when borrowing constraints are binding. Thus, our results reveal an international dimension of the US financial accelerator mechanism: financial frictions give rise to an amplification of financial shocks originating in the US, and facilitate their spillover across the globe. These results draw attention to the negative externalities imposed on the global economy via frictions in financial intermediation in the United States.

Appendix A: MLE estimation of the TVAR

The reduced form of the TVAR model is given by:

$$Y_t = \begin{cases} \Phi^1(L)Y_t + u_t^1 & \text{if} \quad rp_{t-d} < \gamma, \\ \Phi^2(L)Y_t + u_t^2 & \text{if} \quad rp_{t-d} \geq \gamma, \end{cases} \tag{2}$$

where $\Phi^1(L) = (I - A^1)^{-1}\Theta^1(L)$ and $\Phi^2(L) = (I - A^2)^{-1}\Theta^2(L)$ are p_1-order (resp. p_2-order) lag-polynomial matrices of the reduced form coefficients (where $p_1; p_2 \in \mathbb{N}$), and where $u_t^1 \sim (0, \Sigma_u^1)$ and $u_t^2 \sim (0, \Sigma_u^2)$ are vectors of reduced form Gaussian white noise forecast errors, with $\Sigma_u^1 = E(u_t^1 u_t^{1'})$ and $\Sigma_u^2 = E(u_t^2 u_t^{2'})$ positive definite. The reduced form parameters are estimated using the maximum likelihood estimator (MLE) described in Galvao (2006). This entails computing the constrained MLE for $\Phi^1(L)$, $\Phi^2(L)$, Σ_u^1, and Σ_u^2, holding d and γ fixed. For a given delay d and threshold value γ, the MLE are the OLS estimators given by:

$$\begin{bmatrix} \Phi_1^1 \\ \Phi_2^1 \\ \vdots \\ \Phi_{p_1}^1 \end{bmatrix}' = \left(\left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_1} \end{bmatrix}' D_t^1 \right)' \left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_1} \end{bmatrix}' D_t^1 \right) \right)^{-1} \left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_1} \end{bmatrix}' D_t^1 \right)' Y_t$$

and

$$\begin{bmatrix} \Phi_1^2 \\ \Phi_2^2 \\ \vdots \\ \Phi_{p_2}^2 \end{bmatrix}' = \left(\left(\left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_2} \end{bmatrix}' D_t^2\right)' \left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_2} \end{bmatrix}' D_t^2\right)\right)^{-1} \left(\begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p_2} \end{bmatrix}' D_t^2\right)' Y_t,$$

where $D_t^1 = I(rp_{t-d} < \gamma)$ and $D_t^2 = I(rp_{t-d} \geq \gamma)$ are indicator functions. The estimated residuals are obtained as: $\hat{u}_t^1 = Y_t D_t^1 - ([Y'_{t-1}, Y'_{t-2}, ..., Y'_{t-p_1}]D_t^1)[\hat{\Phi}^1{}_1, \hat{\Phi}^1{}_2, ..., \hat{\Phi}^1{}_{p_1}]$ and $\hat{u}_t^2 = Y_t D_t^2 - ([Y'_{t-1}, Y'_{t-2}, ..., Y'_{t-p_2}]D_t^2)[\hat{\Phi}^2{}_1, \hat{\Phi}^2{}_2, ..., \hat{\Phi}^2{}_{p_2}]$. Finally, the MLEs for the covariance matrices are $\hat{\Sigma}_u^1 = 1/T^1 \sum_{t=1}^{T^1} \hat{u}_t^1 \hat{u}_t^{1'}$ and $\hat{\Sigma}_u^2 = 1/T^2 \sum_{t=1}^{T^2} \hat{u}_t^2 \hat{u}_t^{2'}$, where $T^1 + T^2 = T$.

The model is estimated for all possible values of d and γ on an equally spaced grid of rp_{t-d}. The MLE for $\hat{d}$ and $\hat{\gamma}$ are then obtained by solving the following optimization problem:

$$(\hat{\gamma}, \hat{d}) = \min_{\substack{\gamma_L \leq \gamma \leq \gamma_U \\ 1 \leq d \leq d_{max}}} \left(\frac{T^1}{2}\log(|\Sigma_u^1|) + \frac{T^2}{2}\log(|\Sigma_u^2|),\right).$$

where γ_L is the 15%th percentile and γ_U is the 85%th percentile of the empirical distribution of rp_{t-d}. Hence, following Balke (2000), we restrict the search region such that at least 15% of the observations (plus the number of parameters) are in each regime.

Appendix B: Model selection criteria

The heteroskedasticity-robust SupLM statistic for the null hypothesis of a linear VAR against the TVAR alternative can be obtained as follows (see Hansen and Seo, 2002). Let Y^1 and Y^2 be the matrices of the stacked rows $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p_1})D_t^1$ and $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p_2})D_t^2$, respectively, let ξ^1 and ξ^2 be the matrices of the stacked rows $\tilde{u}_t \otimes (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p_1})D_t^1$ and $\tilde{u}_t \otimes (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p_2})D_t^2$, respectively, with $\tilde{u}_t$ the reduced form residual vector from the restricted (linear) VAR model. Furthermore, define the outer product matrices $M^1 = I_m \otimes Y^{1'}Y^1$, $M^2 = I_m \otimes Y^{2'}Y^2$, $\Omega^1 = \xi^{1'}\xi^1$, and $\Omega^2 = \xi^{2'}\xi^2$. The Eicker-White covariance matrix estimators for vec($\hat{\Phi}^1$) and vec($\hat{\Phi}^1$) can be defined as $\hat{V}^1 = (M^1)^{-1}\Omega^1(M^1)^{-1}$ and $\hat{V}^2 = (M^2)^{-1}\Omega^2(M^2)^{-1}$, respectively, from which the heteroskedasticity-robust LM statistic is given by:

$$\text{LM} = \text{vec}(\hat{\Phi}^1 - \hat{\Phi}^2)'(\hat{V}^1 + \hat{V}^2)^{-1}\text{vec}(\hat{\Phi}^1 - \hat{\Phi}^2), \tag{3}$$

which is the test statistic for a given value of γ. The model is estimated by OLS for each possible γ as described above, and the SupLM statistic is given by the supremum of the

LM statistics over the search region $\gamma_L \leq \gamma \leq \gamma_U$:

$$\text{SupLM} = \sup_{\gamma_L \leq \gamma \leq \gamma_U} \text{LM}. \tag{4}$$

Following Altissimo and Corradi (2002), Galvao (2006), and Artis et al. (2007), we use the bounded supWald (BW) and bounded supLM (BLM) statistics as additional model selection criteria. The BW statistic is given by:

$$\text{BW} = \frac{1}{2\log(\log(T))} \left(\sup_{\gamma_L \leq \gamma \leq \gamma_U} T \left(\frac{SSR^{lin} - SSR^{nlin}(\gamma)}{SSR^{nlin}(\gamma)} \right) \right)^{\frac{1}{2}},$$

and the BLM is given by:

$$\text{BLM} = \frac{1}{2\log(\log(T))} \left(\sup_{\gamma_L \leq \gamma \leq \gamma_U} T \left(\frac{SSR^{lin} - SSR^{nlin}(\gamma)}{SSR^{lin}} \right) \right)^{\frac{1}{2}}.$$

SSR^{lin} is the the sum of squared residuals under the linear VAR null, and $SSR^{nlin}(.)$ is the sum of squared residuals under the TVAR alternative hypothesis. The statistics BW and BLM provide the asymptotic bounds on the supremum of the Wald and LM statistics computed over a grid $\gamma_L \leq \gamma \leq \gamma_U$ of possible values for the threshold γ. The TVAR model is chosen over the linear VAR if BW > 1 and, similarly, if BLM > 1. This model selection rule ensures that type I and type II errors are asymptotically zero.

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