Financial Shocks, Credit Regimes, and Global Spillovers*

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Abstract

We investigate whether credit constraints facilitate the international propagation of financial shocks that originate from the United States. The US economy is modeled jointly with global macro and financial variables using a threshold vector autoregression. This model captures regime-dependent dynamics conditional on the tightness of credit market conditions, gauged by a risk premium on US corporate bonds. The economy switches from a regime of unconstrained access to credit to one characterized by tight credit whenever the bond risk premium exceeds a critical threshold. Our results reveal that US financial shocks lead to a tightening of global financial conditions and to a decline in global trade, which trigger a significant worldwide output contraction in periods when borrowers face stringent credit constraints.

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

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1 Introduction

The 2007-08 turmoil in US financial markets gave rise to a credit crunch with widespread effects on the global economy. However, the link between credit market conditions and global spillovers is not yet fully understood. We provide new insights into the international transmission of financial shocks by studying the amplification mechanisms arising from credit constraints that bind in times of crisis. Our empirical results reveal that US financial shocks propagate across the globe predominantly in times when credit is scarce.

A consensus seems to emerge from structural models that "occasionally binding" financial constraints are central to understanding the nonlinearities observed during financial crisis episodes; see e.g. Mendoza (2010), Bianchi (2011), Brunnermeier and Sannikov (2014), and Perri and Quadrini (2014). Specifically, this strand of the literature predicts that economies are resilient to shocks as long as the flow of credit is unconstrained, however, binding credit constraints can give rise to aggregate economic contraction. Moreover, recent studies have shown that financial frictions lead to an amplification of cross-border shocks, and structural models featuring such frictions provide a more realistic picture of international macroeconomic fluctuations; see e.g. Krugman (2008), Devereux and Yetman (2010, 2011), Olivero (2010), Kollmann et al. (2011), and Dedola and Lombardo (2012). Empirical models that ignore nonlinear amplification mechanisms may therefore deliver inaccurate estimates of cross-country spillovers.

The novelty of this paper is to incorporate nonlinear features into an empirical model of international financial spillovers. To that end, we depart from the existing literature in two directions. First, we trace the regime-specific effects of financial shocks using a threshold vector autoregression (TVAR) that distinguishes between normal and tight credit regimes. Second, we model the US economy jointly with global macroeconomic and financial variables in the TVAR. In contrast to models in which regime switching is governed by a latent Markov-process, transition across regimes in the TVAR is determined directly by the degree of credit market frictions in the US economy. Specifically, whenever the tightness of credit exceeds an endogenously estimated threshold level, the economy shifts from a state characterized by unconstrained access to credit to a regime in which borrowers face stringent credit constraints. The VAR dynamics as well as the volatility of shocks varies across these two regimes, which enables us to study regime-specific financial spillovers.

Credit market conditions are measured by the excess bond premium (EBP) in the US corporate bond market proposed by Gilchrist and Zakrajsek (2012). The EBP reflects 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.[1] The EBP thus provides a useful gauge of credit supply conditions in the US economy. In particular, Gilchrist and Zakrajsek (2011, 2012) argue that fluctuations in the EBP give an adequate description of the disruptions in the financial intermediation process. Using a DSGE model, they show that an increase in the EBP reflects a reduction in the risk-bearing capacity of the financial sector, which raises the cost of external finance for non-financial borrowers, leading to a decline in spending and production.

We study the nonlinear propagation of EBP shocks in a baseline model for the US economy comprised of output, prices, credit, the federal funds rate, and the excess bond premium. The baseline model is subsequently augmented with US and global variables to study a multitude of different transmission channels. EBP shocks are recovered via the recursive identification scheme proposed by Gilchrist and Zakrajsek (2011), which assumes that the EBP reacts without delay to all shocks hitting the economy. Our results continue to hold when the EBP shock is identified via sign restrictions on the estimated impulse responses. The restrictions imposed interpret an unexpected rise in the EBP as an adverse shock to the supply of credit, in line with Gilchrist and Zakrajsek (2011) and Peersman (2012).

Our empirical findings reveal a strong asymmetry in the macroeconomic responses to an EBP shock upon distinguishing between normal and tight credit regimes. There is no significant response of output and prices to a rise in the EBP when borrowers have unconstrained access to credit, even though real credit and the fed funds rate decline. On the contrary, an unexpected rise in the EBP is detrimental for the macroeconomy when credit is scarce. In the tight credit regime, a 10 basis points (bp) rise in the EBP acts as a negative credit supply shock accompanied by a decline in real credit by about 1-2 percentage points (pp) – depending on our identifying assumptions – within two years after the shock. The federal funds rate falls by about 10 bp, which suggests that monetary policy takes an accommodative stance in the face of tightening financial conditions. The EBP shock also induces an 0.1 pp decline in consumer prices and an 0.5 pp contraction of industrial output. Finally, upon adding several credit spreads to the

[1] 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.

baseline model, we find that these rise significantly in response to an EBP shock. These outcomes suggest that a tightening of credit market conditions prompts banks to ration lending, which forces firms and households to postpone investment and consumption plans under binding credit constraints. A range of global variables is added one-at-a-time to the baseline model to capture the international effects of an EBP shock. Remarkably, an unexpected rise in the EBP leads to a significant worldwide output contraction in the tight credit regime, while global output reacts insignificantly to the US financial shock in the normal credit regime. Deteriorating global financial conditions and a decline in global trade serve as conduits for the US financial shock in the tight credit regime, while all transmission channels remain muted in normal times.

We contribute to three strands of the literature. First, our econometric approach provides an empirical counterpart of the recently developed macroeconomic models that feature occasionally binding financial constraints; see e.g. Mendoza (2010), Bianchi and Mendoza (2010), Bianchi (2011), and Brunnermeier and Sannikov (2014). In particular, our paper is closely related to Perri and Quadrini (2014), who study the international propagation of financial shocks in a two-country model with occasionally binding constraints that give rise to multiple equilibria. Our results complement this theoretical literature with empirical evidence on regime-specific spillover effects that arise from financial frictions. Second, our paper contributes to a growing literature on macro-financial linkages; see e.g. Gilchrist and Zakrajsek (2012) and Meeks (2012). Macro-financial models often fail to capture nonlinear amplification effects and feedback loops. Balke (2000) constitutes an exception, however, his paper focuses on credit frictions solely in a closed economy setup. Our paper departs from existing studies by accounting for nonlinearities in an empirical model of international spillovers. Finally, our work is also related to a battery of papers on the international transmission of financial shocks; see e.g. Helbling et al. (2011), Bagliano and Morana (2012), and Cettorelli and Goldberg (2012). The paper by Helbling et al. (2011) on the global transmission of US credit market shocks is closest to ours, albeit they use a constant-parameter VAR model that lacks nonlinear features.

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 it concludes the paper.

2 Methodology

2.1 The threshold vector autoregressive model

Our point of departure is a 5-variate system for the US economy, $Y_t = (q_t, \pi_t, c_t, i_t, ebp_t)$, that comprises the growth rate of industrial production (q_t), consumer price inflation (π_t), the growth rate of real credit (c_t), the federal funds rate (i_t), and the excess bond premium (ebp_t). Y_t is subsequently augmented with a range of global macro and financial variables in order to capture global spillovers. We assume that Y_t follows a threshold vector autoregressive process given in structural form by:

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

for $t \in \{1, ..., T\}$, where ebp_{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, regime-specific shocks ε_t^1 and ε_t^2 are normally distributed with zero mean and regime-dependent positive definite covariance matrices $\Sigma_\varepsilon^1 = E(\varepsilon_t^1 \varepsilon_t^{1'})$ and $\Sigma_\varepsilon^2 = E(\varepsilon_t^2 \varepsilon_t^{2'})$. The model is estimated using the maximum likelihood estimator (MLE) described in Appendix A.

Whenever the EBP crosses a threshold level γ, the economy shifts from a state in which access to credit is unconstrained ("normal credit regime") into one where borrowers face stringent credit constraints ("tight credit regime"). The VAR dynamics as well as the volatility of shocks can vary across these two regimes. We estimate the threshold $\hat{\gamma}_{US}$ endogenously from the above described model for the US economy. Subsequently, we augment Y_t with variables representing the global economy, and the TVAR is re-estimated with $\hat{\gamma}_{US}$. This approach ensures that the identified regimes reflect distressed credit conditions in the US economy.

We investigate the effects of an unexpected rise in the US excess bond premium. Conditional on the threshold γ, the TVAR model reduces to a piecewise linear VAR. Therefore, we can obtain impulse response functions (IRFs) which describe the dynamic effects of EBP shocks within each regime, under the assumption that the economy resides in the same regime for the duration of the response (see e.g. Ehrmann et al., 2003; Candelon and Lieb, 2013).[2] Identification of regime-specific shocks can be achieved by

[2]Even though this approach may have the limitation that switches from one regime to another are not explicitly modeled, it has the important advantage that, in contrast to the generalized IRF occasionally used in the literature, it enables structural identification of EBP shocks.

imposing orthogonality restrictions on the contemporaneous relationships A^1 and A^2.

We employ two alternative identification schemes to recover EBP shocks from the data.[3] In the baseline, EBP shocks are identified via the recursive scheme proposed by Gilchrist and Zakrajsek (2011, 2012), which is implemented by performing a Cholesky decomposition of the regime-specific reduced-form covariance matrices Σ_u^s, where $s = 1, 2$.[4] The identifying assumption entails that the EBP responds without delay to all macroeconomic and policy shocks hitting the economy, while the macroeconomy reacts with a slack to EBP shocks. This identification scheme delivers a lower bound on the estimated effects of EBP shocks. Moreover, it acknowledges the high-frequency nature of financial markets, which constitutes a standard approach in the VAR literature.

Our second identification approach exploits the fact that the EBP captures credit supply conditions in the US economy, as argued by Gilchrist and Zakrajsek (2011, 2012). Hence, an unexpected rise in the EBP can be thought of as a tightening in the supply of credit. This shock is isolated from other macro and financial shocks, and in particular from monetary policy induced changes in credit supply by imposing a combination of zero and sign restrictions on the estimated impulse responses. Specifically, in line with Peersman (2012), this shock is assumed to have only a lagged impact on output and prices, i.e. the contemporaneous impact on both variables is restricted to be zero. Moreover, a tightening of credit supply ($ebp_t \geq 0$) is accompanied by a decline in the real volume of loans ($c_t \leq 0$) and by a drop in the federal funds rate ($i_t \leq 0$). Table 1 summarizes the identifying assumptions. All restrictions are assumed to hold for at least 6 months following the shock, and all other shocks hitting the economy are assumed to display a different pattern.

[Table 1 about here.]

The identifying restrictions are implemented using the method by Rubio-Ramirez et al. (2010). It is well known that sign restrictions do not allow us to achieve unique identification of shocks. Hence, we draw rotation matrices until 500 of them yield shocks consistent with our sign restrictions. We adopt the median target approach to pick among all models the one which yields impulse responses closest to the median response (Fry and Pagan, 2011).

[3]We attach an economic interpretation solely to the EBP 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.

[4]In particular, the reduced form covariance matrices can be decomposed as $\Sigma_u^1 = (A^1)^{-1}\Sigma_\varepsilon^1(A^1)^{-1'}$ and $\Sigma_u^2 = (A^2)^{-1}\Sigma_\varepsilon^2(A^2)^{-1'}$, from which the shocks can be recovered as $\varepsilon_t^1 = A^1 u_t^1$ and $\varepsilon_t^2 = A^2 u_t^2$.

3 Empirical results

3.1 Data

We use monthly data between January 1984 and December 2012. Thus, our sample ranges from the ascent of the Great Moderation until the recovery from the global financial crisis. The effective federal funds rate and the excess bond premium enter in levels, and the baseline model also contains the logarithmic difference of the industrial production index, the consumer price index (CPI), and the volume of commercial and industrial loans issued by all US commercial banks, deflated by the CPI to obtain real credit. Time series for the US are obtained from the Federal Reserve Bank of St. Louis and from Gilchrist and Zakrajsek (2012).[5]

We augment the baseline 5-variate VAR one-at-a-time with six variables that capture transmission channels of EBP shocks within the US economy. In particular, we add non-financial leverage calculated by the Federal Reserve Bank of Chicago as a (standardized) weighted average of the ratio of non-financial business debt outstanding to GDP and the ratio of household mortgage and consumer debt outstanding to the sum of residential investment and personal consumption expenditures on durable goods. Furthermore, we gauge US credit market conditions by the high-yield bond spread (the difference between Moody's Baa rated long-term corporate bonds and 10-year Treasuries), by the Gilchrist-Zakrajsek spread, and by an index of broader credit conditions which is a subindex of the Chicago Fed's National Financial Conditions Index (NFCI). In addition we add the S&P 500 stock price index.

Next, we add aggregate global output to the baseline 5-variate VAR in order to study the international dimensions of EBP shocks. Subsequently, the 6-variate VAR is augmented one-at-a-time with seven global macro and financial variables to shed light on international transmission channels. These include global consumer prices, the global short-term nominal interest rate, global financial uncertainty, the global corporate credit spread, the nominal exchange rate, global trade, and the oil price. Global variables are proxied by weighted averages of time series for 18 major economies. The countries included are Argentina, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, India, Italy, Japan, Korea, Mexico, the Netherlands, Spain, Sweden, and the United Kingdom. The weights reflect the average overall size of the economy over the estimation period, and they are based on the time mean of PPP-adjusted annual real GDP from the Penn World Tables.

[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.

Global output is measured by industrial production data obtained from the OECD. Global financial uncertainty is captured by the weighted average realized stock market volatility, 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. The global interest rate is computed as the weighted average of monetary policy rates. We use 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 take 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 its 18 counterparts (deflated by US CPI), obtained from the IMF Direction of Trade statistics.

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 2 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 model. Again, the equation-wise supremum statistics speak unequivocally in favor of the nonlinear model.

[Table 2 about here.]

3.3 Credit regimes

We estimate the TVAR with $p_1 = 5$ lags in the normal credit regime and $p_2 = 3$ lags in the tight credit regime, 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. 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 the savings and loan crisis of 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 relative financial stability 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 recent global financial crisis. The credit crunch associated with the global financial crisis constitutes the last major tight credit regime.

[Figure 1 about here.]

3.4 Structural analysis

We trace the effects of an EBP shock on the US and the global economy, conditional on whether the US credit market resides in a normal or tight credit regime. To capture asymmetries across regimes, we report regime-specific median impulse responses to a 10 bp rise in the EBP together with 68% bootstrapped confidence bands obtained from 1000 draws. All IRFs are shown for 36 months.

3.5 Regime-specific effects of EBP shocks on the US economy

Figure 2 shows the regime-specific IRFs to a 10 basis point rise in the EBP from the baseline TVAR identified via Cholesky decomposition. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

An unexpected rise in the EBP dies out after about one year in both regimes. The federal funds rate falls significantly by about 5 bp in the normal regime and by about 10 bp in the tight regime within a year after the shock, which suggests that monetary policy typically takes an accommodative stance in the face of tightening financial conditions. However, we find a strong asymmetry in the strength of the macroeconomic responses across regimes. In periods when borrowers have unconstrained access to credit, an EBP shock barely exerts an effect on output, prices or real credit. Hence, the monetary expansion seems to contain the financial shock in times when the financial system is in good health. On the contrary, the EBP shock is detrimental for the real economy if credit is scarce. Commercial and industrial lending declines by nearly 1 pp, while output undergoes an 0.5 pp contraction within a year after the shock. Consumer prices decline persistently by approximately 1 percentage point.

Our empirical results remain qualitatively unchanged when the EBP shock is identified via a combination of zero and sign restrictions, as illustrated in Figure 3. Remarkably, both credit and the fed funds rate decline upon impact and their drop is more accentuated when the contemporaneous zero restrictions imposed by the recursive Cholesky scheme are removed.

The macroeconomic downturn observed in the tight credit regime suggests that a rise in the EBP induces banks to ration lending, which forces firms and households to postpone investment and consumption plans under binding credit constraints. In support of these arguments, Figure 4 shows the IRFs from TVAR models augmented one-at-a-time with variables that capture credit market conditions in the US economy. In the tight credit regime, an adverse EBP shock is associated with tighter financial conditions in high-yield and broader credit markets. In response to this credit crunch, the non-financial sector embarks on a protracted de-leveraging process and stock prices decline.

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

3.6 Regime-specific effects of EBP shocks on the global economy

Figure 5 shows the regime-specific IRFs to a 10 basis point rise in the EBP from the TVAR augmented with global output identified via Cholesky decomposition, while Figure 6 depicts the IRFs from the 6-variate TVAR identified through sign restrictions. Again, the same picture emerges across different identification schemes. A rise in the EBP facilitates a significant international output contraction, and there is a twofold global output decline in the tight credit regime (amounting to about 0.4 pp) compared to normal times.

[Figure 5 about here.]

[Figure 6 about here.]

Figure 7 depicts the impulse responses to an EBP shock of seven global variables added to the 6-variate TVAR one-at-a-time.[6] Again, we find a clear asymmetry across US credit regimes. Tightening credit market conditions in the US generate worldwide repercussions under binding credit constraints due to trade and financial links with the rest of the world, while all transmission channels remain muted in normal times. Remarkably, exchange rates do not seem to be an important transmission channel for EBP shocks. However, prices fall, global financial volatility rises, and corporate credit spreads widen significantly after an EBP shock in the tight regime. Thus, 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). Furthermore, US trade with the rest of the world shrinks for about 2.5 years after the shock, and the oil price drops by 1.5 pp under binding credit constraints. Finally, the global economic downturn is accompanied by a worldwide monetary expansion, amounting to a 5 basis point decrease in the global interest rate. On balance, these findings highlight that credit constraints amplify the effects of US financial shocks on the global economy.

[Figure 7 about here.]

4 Conclusion

Financial frictions are often embedded in macroeconomic models, however, most empirical studies on macro-financial linkages resort to linear models that fail to 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 model economic activity in the US jointly with global macro and financial variables using a threshold vector autoregressive model. This model captures regime-dependent dynamics conditional on the tightness of credit market conditions Transition from a state of unconstrained financial intermediation to a regime characterized by binding financial constraints arises endogenously in this framework. We capture US credit market conditions by an excess bond risk premium proposed by Gilchrist and Zakrajsek (2012). This

[6] We only show the responses of the additional global variables, as the remaining IRFs from the TVAR are largely robust to variations of the model.

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 crisis of the 1980s and early 1990s. The second episode occurs in the early 2000s, around the Enron, Y2K, and 9/11 debacles and following the burst of the dotcom bubble. Finally, our results suggest that the 2007-09 crisis is associated with a severe credit crunch.

We find that financial frictions amplify business cycle fluctuations within as well as across economies. The effects of US risk premium shocks on the global economy are measured by regime-specific impulse response functions. Upon distinguishing between normal and tight credit regimes, we uncover a strong asymmetry in the strength of the structural impulse 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. Hence, our empirical results reveal an international dimension of the US financial accelerator mechanism, which draws 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:

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

and

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

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.

References

Altissimo, F. and V. Corradi (2002). Bounds for inference with nuisance parameters present only under the alternative. *Econometrics Journal 5*, 494–519.

Artis, M., A. Galvao, and M. Marcellino (2007). The transmission mechanism in a changing world. *Journal of Applied Econometrics 22*, 39–61.

Bagliano, F. and C. Morana (2012). The Great Recession: US dynamics and spillovers to the world economy. *Journal of Banking and Finance 36*, 1–13.

Balke, N. (2000). Credit and economic activity: Credit regimes and nonlinear propagation of shocks. *Review of Economics and Statistics 82*(2), 344–349.

Bianchi, J. (2011). Overborrowing and systemic externalities in the business cycle. *American Economc Review 101*(7), 3400–3426.

Bianchi, J. and E. Mendoza (2010). Overborrowing, financial crises, and 'macro-prudential' policies. NBER Working Paper No. 16091.

Brunnermeier, M. K. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economc Review 104*(2), 379–421.

Candelon, B. and L. Lieb (2013). Fiscal policy in good and bad times. *Journal of Economic Dynamics and Control 37*, 2679–2694.

Cettorelli, N. and L. Goldberg (2012). Liquidity management of U.S. global banks: Internal capital markets in the great recession. *Journal of International Economics 88*, 299–311.

Dedola, L. and G. Lombardo (2012). Financial frictions, financial integration and the international propagation of shocks. *Economic Policy 27*(70), 319–359.

Devereux, M. B. and J. Yetman (2010). Leverage constraints and the international transmission of shocks. *Journal of Money, Credit and Banking 42*(6), 71–105.

Devereux, M. B. and J. Yetman (2011). Evaluating international financial integration under leverage constraints. *European Economic Review 55*, 427–442.

Ehrmann, M., M. Ellison, and N. Valla (2003). Regime-dependent impulse response functions in a Markov-switching vector autoregression model. *Economics Letters 78*, 295–299.

Federal Deposit Insurance Corporation (1997). History of the eighties – Lessons for the future. http://www.fdic.gov/bank/historical/history/.

Fry, R. and A. Pagan (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature 49*, 1–24.

Galvao, A. (2006). Structural break threshold VARs for predicting US recessions using the spread. *Journal of Applied Econometrics 21*, 463–487.

Gilchrist, S. and E. Zakrajsek (2011). Monetary policy and credit supply shocks. *IMF Economic Review 59*(2), 195–232.

Gilchrist, S. and E. Zakrajsek (2012). Credit spreads and business cycle fluctuations. *American Economc Review 102*(4), 1692–1720.

Hansen, B. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica 64*, 413–430.

Hansen, B. and B. Seo (2002). Testing for two-regime threshold cointegration in vector error correction models. *Journal of Econometrics 110*, 293–318.

Helbling, T., R. Huidrom, M. A. Kose, and C. Otrok (2011). Do credit shocks matter? A global perspective. *European Economic Review 55*, 340–353.

Kollmann, R., Z. Enders, and G. Müller (2011). Global banking and international business cycles. *European Economic Review 55*, 407–426.

Krugman, P. (2008). The international finance multiplier. mimeo.

Meeks, R. (2012). Do credit market shocks drive output fluctuations? Evidence from corporate bond spreads and defaults. *Journal of Economic Dynamics and Control 36*, 568–584.

Mendoza, E. (2010). Sudden stops, financial crises, and leverage. *American Economic Review 100*(5), 1941–1966.

Olivero, M. (2010). Market power in banking, countercyclical margins and the international transmission of business cycles. *Journal of International Economics 80*, 292–301.

Peersman, G. (2012). Bank lending shocks and the euro area business cycle. Mimeo.

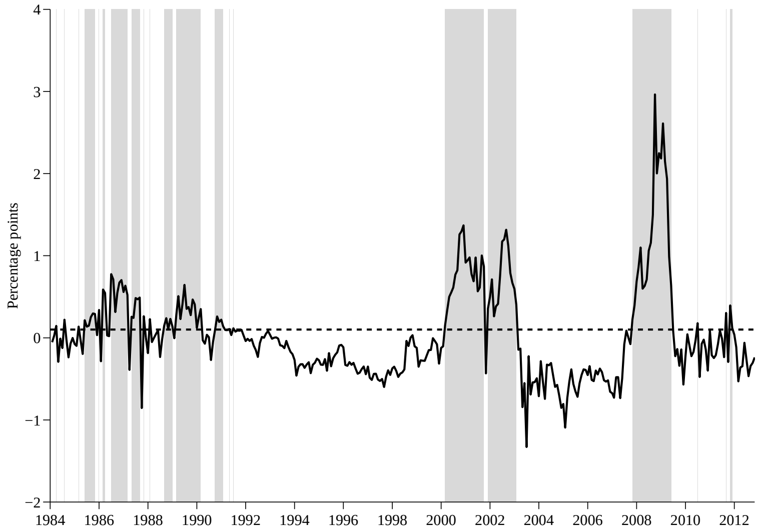
Perri, F. and V. Quadrini (2014). International recessions. mimeo.

Rubio-Ramirez, J. F., D. F. Waggoner, and T. Zha (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *Review of Financial Studies 77*(2), 665–696.

Tsay, R. (1998). Testing and modeling multivariate threshold models. *Journal of the American Statistical Association 93*, 1188–1202.

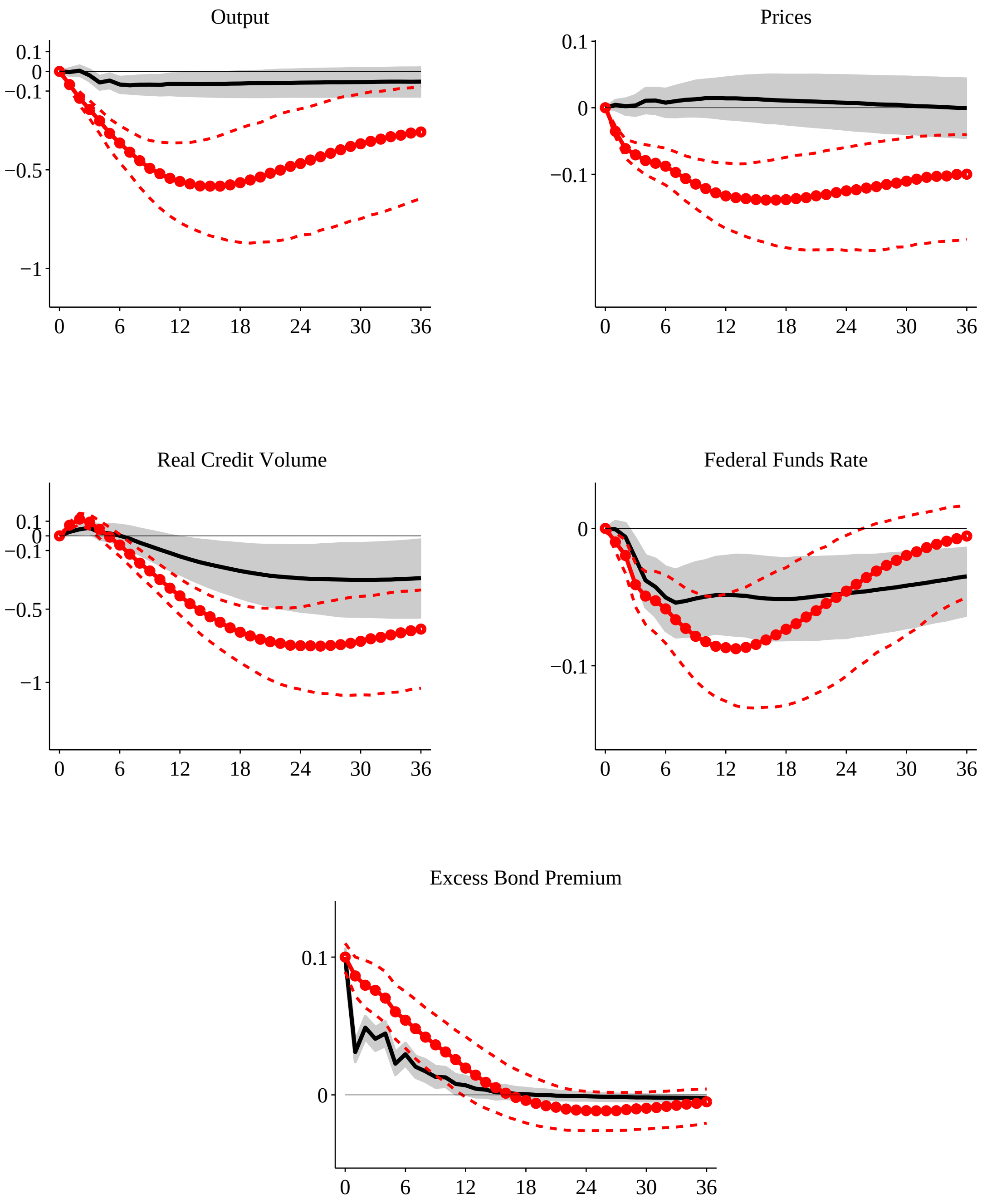
Wong, C. and W. Li (1998). A note on the corrected Akaike information criterion for threshold autoregressive models. *Journal of Time Series Analysis 19*(1), 113–124.

Figure 1: Excess bond premium and financial regimes



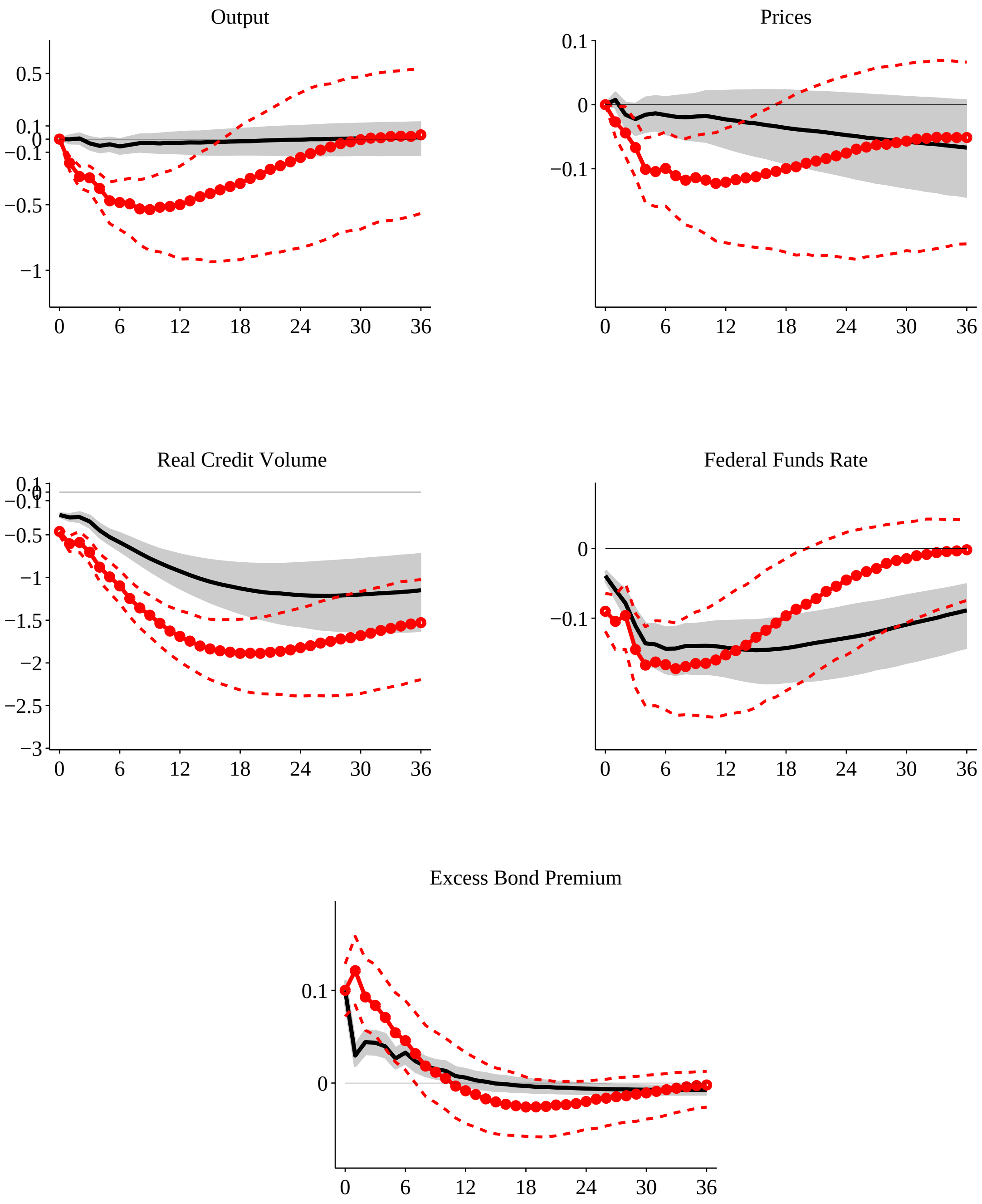
Note: The solid line depicts the lagged excess bond premium and the dashed line corresponds to the estimated threshold value ($\hat{\gamma}_{US} = 0.1004$). Tight credit regimes are shaded in grey. Sample: January 1984 - December 2012.

Figure 2: Effects of an EBP shock identified via Cholesky decomposition



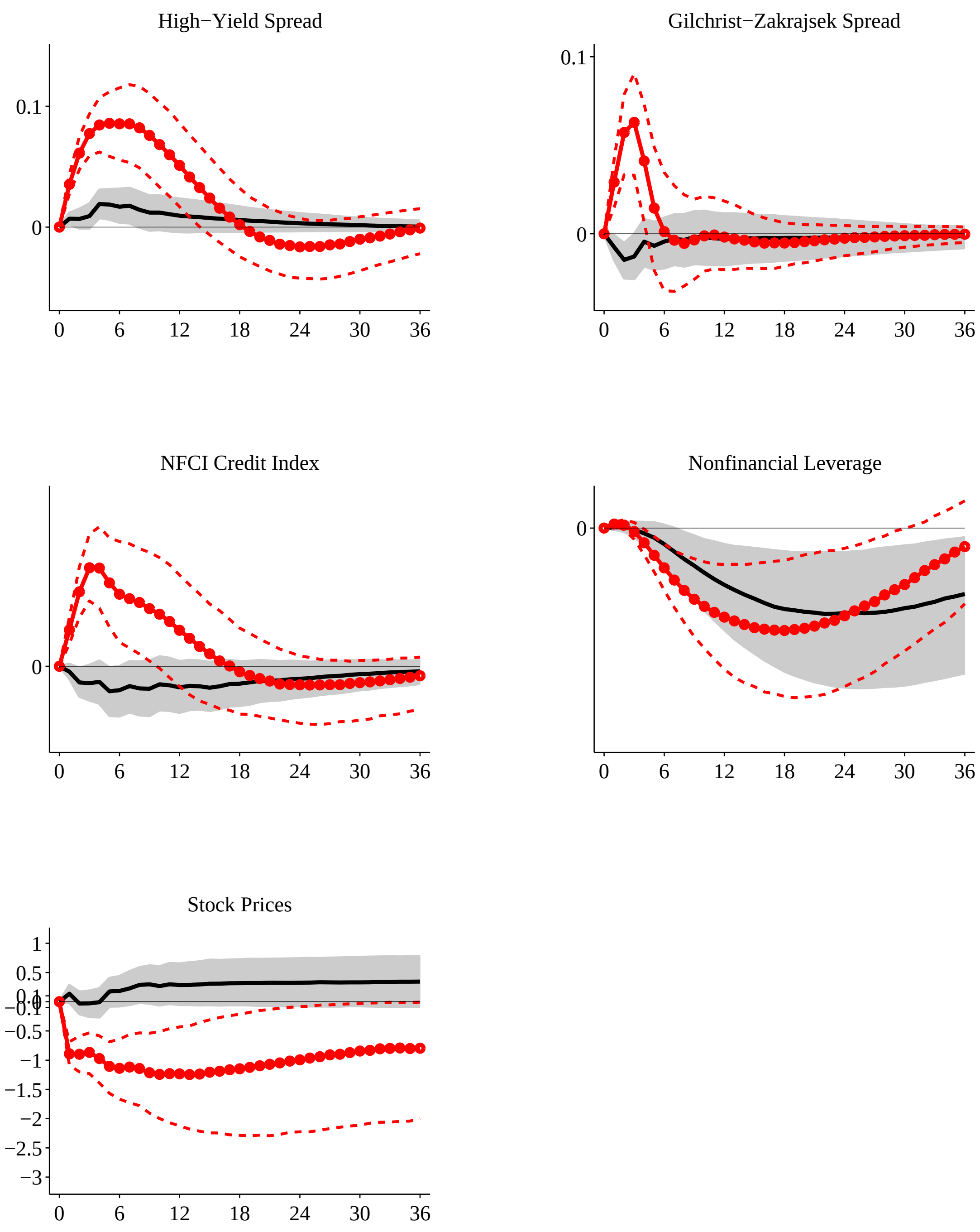
Note: Impulse responses to a 10 basis point rise in the EBP from the baseline TVAR identified via Cholesky decomposition. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Figure 3: Effects of an EBP shock identified via sign restrictions



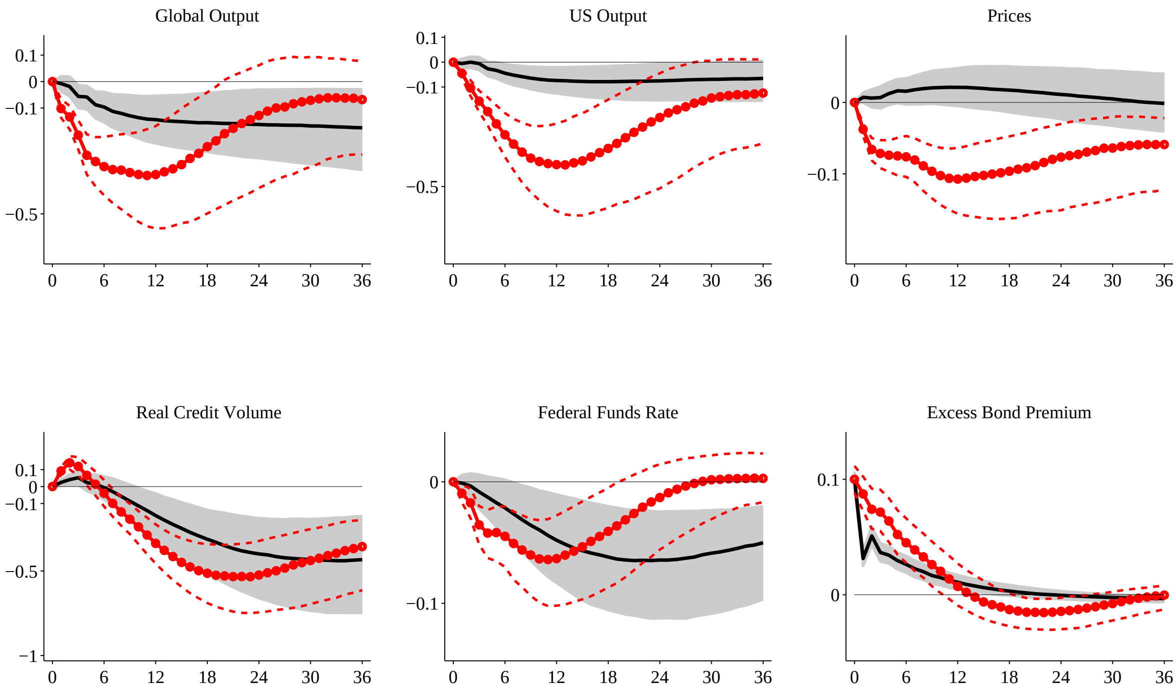
Note: Impulse responses to a 10 basis point rise in the EBP from the baseline TVAR identified via sign restrictions. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Figure 4: Impulse responses of US credit markets to an EBP shock



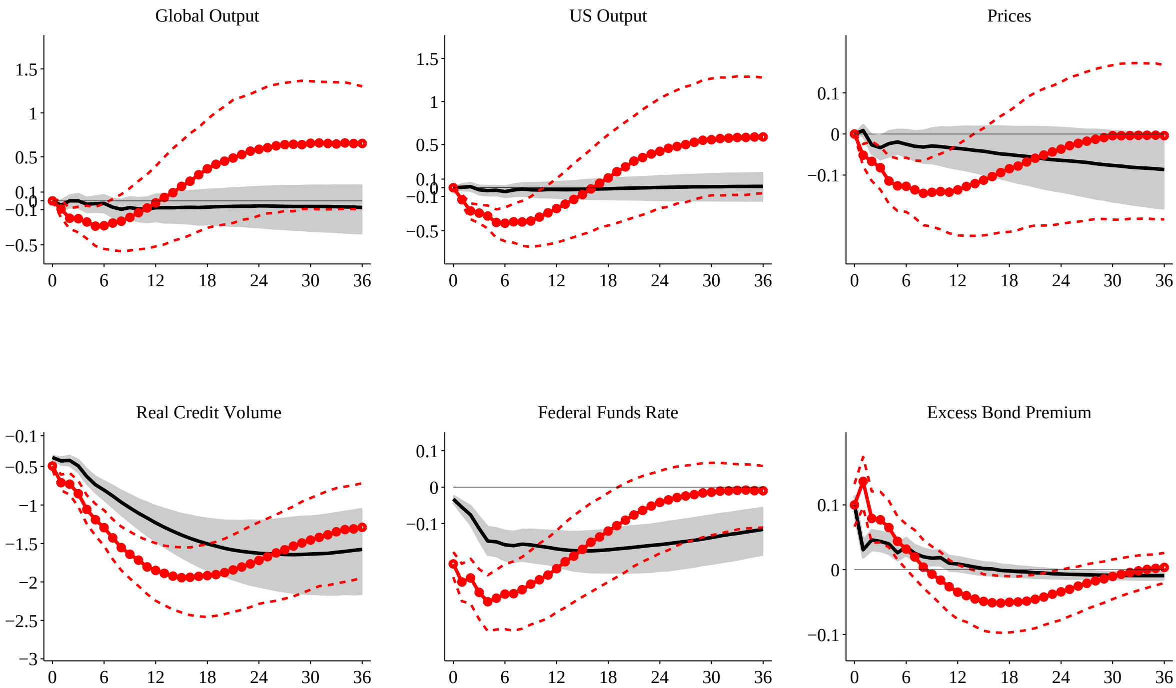
Note: Impulse responses to a 10 basis point rise in the EBP identified via Cholesky decomposition. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Figure 5: Effects of an EBP shock identified via Cholesky decomposition



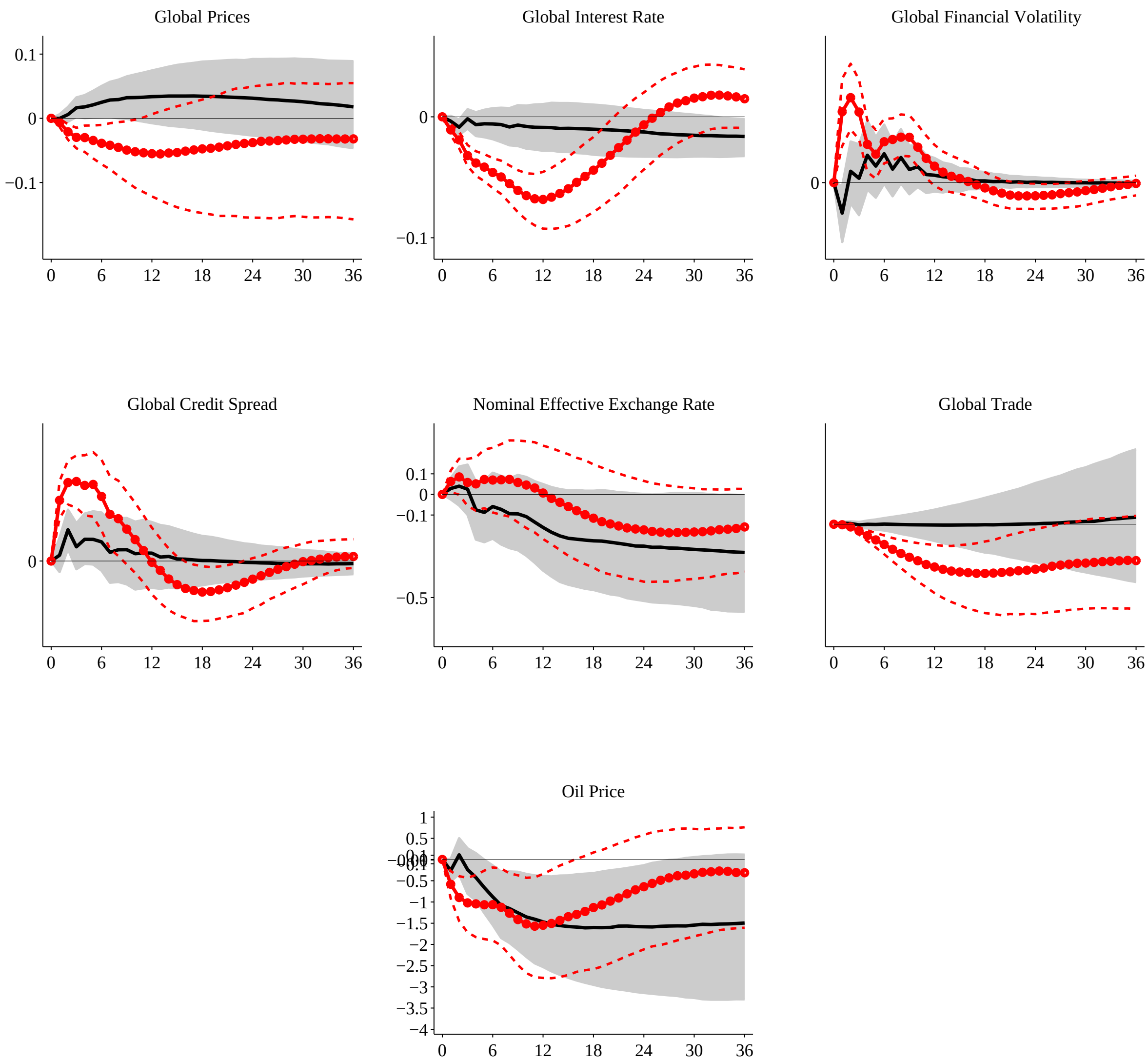
Note: Impulse responses to a 10 basis point rise in the EBP from the 6-variate TVAR identified via Cholesky decomposition. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Figure 6: Effects of an EBP shock identified via sign restrictions



Note: Impulse responses to a 10 basis point rise in the EBP from the 6-variate TVAR identified via sign restrictions. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Figure 7: Impulse responses of global variables to an EBP shock



Note: Impulse responses to a 10 basis point rise in the EBP identified via Cholesky decomposition. The black solid lines are the median impulse responses from the TVAR model in the unconstrained credit regime with shaded areas representing 68% confidence bands based on 1000 draws. The red dotted lines are the median impulse responses from the TVAR model in the tight credit regime with dashed lines representing 68% confidence bands.

Table 1: Identification of EBP shocks via zero and sign restrictions

Response of	q_t	π_t	c_t	i_t	ebp_t
	0	0	≤ 0	≤ 0	≥ 0
Horizons	Contemp.	Contemp.	0-6 M	0-6 M	0-6 M

Note: q_t: output, π_t: prices, c_t: credit volume, i_t: fed funds rate, ebp_t: excess bond premium.

Table 2: Model selection criteria

Selection criterion	q_t	π_t	c_t	i_t	ebp_t
BW	4.174	3.837	4.429	4.898	4.738
BLM	3.878	3.603	4.080	4.437	4.317

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.