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EVOLUTION OF A SMALL OPEN EMERGING ECONOMY'S EXTERNAL VULNERABILITY: EVIDENCE FOR CHILE*

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Abstract

The increase in global economic volatility due to the ongoing crisis in developed countries and its spillovers to the rest of the world has brought renewed relevance to external shocks as a source of business cycles in emerging market economies. This paper analyzes changes in the impact of external shocks in Chile since the 1990s. A novel aspect of our analysis is the use of structural vector autoregressions with time-varying parameters in the context of a small open emerging economy such as Chile. Our main finding is that external shocks have had smaller effects on local economic output at relevant policy horizons after the 1990s. The timing of the estimated changes coincides with major monetary and fiscal policy reforms conducted around 1999-2001, suggesting that those reforms have played an important role in isolating the Chilean economy from external shocks since that time.

Resumen

El aumento de la volatilidad de la economía mundial debido a la actual crisis en los países desarrollados y sus efectos de desborde al resto del mundo ha suscitado una renovada relevancia de los *shocks* externos como fuente de los ciclos económicos en las economías emergentes. Este trabajo analiza los cambios en el impacto de los *shocks* externos en Chile desde los 1990s. Un aspecto novedoso de nuestro análisis es el uso de vectores autorregresivos estructurales con parámetros cambiantes en el tiempo en el contexto de una economía emergente, pequeña y abierta, como la de Chile. Nuestra principal conclusión es que los *shocks* externos han tenido un efecto menor sobre la producción económica local en el horizonte de política relevante después de la década de 1990. La temporalidad de los cambios estimados coincide con importantes reformas de política monetaria y fiscal realizados en torno a 1999-2001, lo que sugiere que estas reformas han jugado un papel importante en el aislamiento de la economía chilena de los shocks *externos* desde entonces.

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1 Introduction

The increase in global economic volatility due to the ongoing crisis in developed countries and its spillovers to the rest of the world has brought renewed relevance to external shocks as a source of business cycles in emerging market economies. Advances in trade integration over the past decades have made changes in external demand conditions and prices even more important than in the past, while financial integration has increased the relevance of capital flows and movements in external financing costs. However, macroeconomic policy reforms conducted in developing countries over time may have provided better insulation from external shocks compared to past crises. With this background, the aim of this paper is to analyze two related dimensions for the case of Chile, that is: (i) the exposure of the local economy to external shocks at different points of time in terms changes in their volatility and their propagation among external variables; and (ii) possible changes in the impact of external shocks on local economic output.

Chile is a particularly interesting case study. As many other developing countries, Chile has become increasingly open to international trade and financial flows over time. Trade integration has strengthened since the early 1990s with the implementation of several free trade agreements that led to a rise in the share of exports in GDP from 28% during 1990-1999 to 39% during 2000-2011. Financial integration has also accelerated over time due to gradual capital account liberalization and a surge in foreign direct investment and portfolio investment during the 1990s, and additional capital inflows concentrated in derivative financial instruments especially since the mid-2000s. While this integration process may have brought important benefits to the Chilean economy, the main downside risk of international economic integration is a potentially enhanced vulnerability to external shocks. However, major reforms were also conducted over the past two decades to limit this downside risk by isolating the Chilean economy at least partially from external shocks. Financial integration was accompanied by an institution-building process to achieve an adequate level of regulation and supervision of the domestic financial system. In addition, a monetary regime based on inflation targeting and a floating exchange rate was introduced in 1999, where the latter is supposed to provide automatic adjustment to external shocks. Finally, a structural balance fiscal rule was applied from 2001 onwards to isolate government spending from transitory changes in commodity export revenues.[1]

The overall balance of the impact of external economic integration and macroeconomic reforms in Chile is not yet clear. On the one hand, one may suspect that external shocks are amplified in a financially and comercially highly integrated economy. On the other hand, macro-

[1] For historical perspectives of financial integration and monetary policy in Chile, see Cifuentes and Desormeaux (2005) and Cowan and De Gregorio (2007). For discussions of Chile's fiscal rule, see Marcel, Tokman, Valdés, and Benavides (2001) (in Spanish); Medina and Soto (2007); Pedersen (2008) (both in English).

economic reforms and instituition-building may have reduced the impact of external shocks on local business cycles, as argued in previous work (see Céspedes, Goldfajn, Lowe, and Valdés, 2006). Altogether, our analysis may therefore contribute to point out possible priorities not only for domestic policy but also for similar emerging countries that might consider the type of integration process or reforms conducted in Chile.

Our analysis is based on structural vector autoregressions (VARs) with time-varying parameters, following the work of Cogley and Sargent (2002, 2005) and Primiceri (2005). The time-varying VAR framework allows for drifting coefficients a changing covariance matrix of the reduced-form innovations, which makes it possible to capture non-linearities and changes in the simultaneous and lagged relationships between macroeconomic variables as well as possible stochastic volatility in the underlying structural shocks. Due to this flexibility, this framework has become increasingly popular in the recent macroeconomic literature.[2] One can conclude from this literature and other contributions, e.g. Sims and Zha (2006) and Stock and Watson (1996), that evidence of structural breaks such as changes in persistence and stochastic volatility abounds in aggregate time series for developed countries. The available evidence for developing countries is however still relatively scarce.

Given our focus on a small open economy, we allow for related restrictions in the empirical model through additional overidentifying cross-equation exclusion restrictions on lagged relationships. It is well-known that the use of such restrictions can have critical implications for a VAR-based assessment of the effects of external shocks in a small open economy, as highlighted by Zha (1999). However, this possibility, where (over)identification relates to lag structure, has not always been acknowledged in time-varying VAR studies for small open economies.[3] Cross-equation restrictions are also useful to address the problem that time-varying VARs tend to be heavily parameterized, because adding time variation of the coefficients and stochastic volatility significantly enlarges the dimension of the model's parameter space which easily exhausts available degrees of freedom and may therefore lead to imprecise estimates. The use of cross-equation restrictions reduces the number of parameters by a multiple of the number of imposed restrictions and thus partially eases this critical dimensionality problem.

The main aspects of our empirical application are as follows. We use monthly data from December 1990 to April 2012, where the higher frequency of the data set than in most previous applications of time-varying VARs helps to further address the dimensionality issue discussed above. The data includes interest rate spreads to measure external financial conditions, the real

[2] A sample of recent studies with applications of time-varying structural VARs includes Bianchi, Mumtaz, and Surico (2009), Canova and Ciccarelli (2009), Canova and Gambetti (2009), Galí and Gambetti (2009), and Kirchner, Cimadomo, and Hauptmeier (2010).

[3] The only exception that we are aware of is a recent study by Liu, Mumtaz, and Theophilopoulou (2011).

price of copper to capture terms of trade changes and an indicator of economic activity/output to gauge the response of the local economy to external shocks. The copper exports sector is the traditional pillar of Chile's economy and has gained additional importance over the past decades: the share of copper in total exports has increased from 30% (85% of mining exports) during the 1990s to 44% (92% of mining exports) during 2000-2011.[4] Copper price fluctuations are thus an ever more important factor of Chile's terms of trade vulnerability. Additional interest in copper price fluctuations stems from the application of Chile's copper-price-related fiscal rule since 2001 as well as high commodity price volatility since the mid-2000s.

We conduct formal model comparisons based on estimated marginal likelihoods to select our preferred model for the empirical analysis. In particular, we compare models with (i) fixed parameters, (ii) drifting coefficients but a fixed covariance matrix of the innovations, (iii) drifting coefficients and univariate stochastic volatility in the innovations, (iv) drifting coefficients and multivariate stochastic volatility that allows for changing impact responses to (standardized) shocks. This model identification step allows to gauge the importance of changes in macroeconomic dynamics and to let different elements of time variation compete with each other. (For instance, changes in business cycle fluctuations in Chile may be driven by changes in the volatility of shocks or also changes in the propagation of shocks, provided that there were any such changes at all). This is an important step, because misspecification of time variation such as omitting relevant elements may imply that time variation is instead erroneously attributed to elements that are allowed to change over time. We also use marginal likelihood comparisons to select the (cross-)lag structure for the empirical model.

Our findings show that, first, an increase in the joint volatility of financial and copper price shocks since the mid-2000s has augmented external uncertainty towards levels observed during earlier emerging market crises. Second, the propagation of financial shocks into copper prices and the associated "pass-through"of financial volatility has increased over time. Third, despite these changes that have enhanced Chile's external exposure, external shocks have had smaller effects on local economic output since the 2000s compared to the 1990s, in particular at horizons above one year. The timing of the estimated changes coincides with the above-mentioned monetary and fiscal policy reforms conducted in 1999-2000, which suggests that those reforms have contributed to isolating the Chilean economy from external shocks since that time.

The remainder of the paper is organized as follows. Section 2 describes the econometric models and the main aspects of their estimation. Section 3 discusses the empirical application in detail. Section 4 presents the empirical results. Section 5 concludes.

[4]Source: Central Bank of Chile's SIETE database (http://sieteweb.bcch.local/siete/secure/cuadros/home.aspx) and authors' own calculations.

2 Econometric models

2.1 General form of the models

We consider a general form of VAR models that permits time-varying parameters and exclusion restrictions on the autoregressive lag structure. Thus, let $y_{i,t}$ denote the observation of variable i at time t and let $x_{i,t}$ be a $k_i \times 1$ vector of explanatory variables for equation i that includes lagged values of the observed variables and any exogenous variables. Further, let $\beta_{i,t}$ be a conformable vector of coefficients, and let $u_{i,t}$ denote an unobserved additive and non-autocorrelated innovation in equation i whose remaining distributional properties are stated below. With these definitions, the model includes a system of observation equations given by

$$y_{i,t} = x'_{i,t}\beta_{i,t} + u_{i,t}, \qquad i = 1, \ldots, n, \qquad t = 1, \ldots, T, \tag{1}$$

An unrestricted VAR of lag order p with an intercept includes p lags of each endogenous variable as right-hand side terms in each equation, that is:

$$x_{1,t} = x_{2,t} = \cdots = x_{n,t} = [1, y_{1,t-1}, , \ldots, y_{1,t-p}, y_{2,t-1}, , \ldots, y_{2,t-p}, \ldots, y_{n,t-1}, \ldots, y_{n,t-p}]'.$$

The model with (1) is however flexible in the sense that coefficient exclusion restrictions can be imposed through different right-hand side terms across individual equations. For example, if $y_{1,t}$ is block exogenous with respect to the remaining endogenous variables, we have instead $x_{1,t} = [1, y_{1,t-1}, \ldots, y_{1,t-p},]'$ and $x_{2,t} = x_{3,t} = \cdots = x_{n,t} = [x'_{1,t}, y_{2,t-1}, \ldots, y_{2,t-p}, \ldots, y_{3,t-1}, \ldots, y_{3,t-p}, \ldots, y_{n,t-1}, \ldots, y_{n,t-p}]'$. Let $k = \sum_{i=1}^{n} k_i$ and define an $n \times 1$ vector of endogenous variables y_t, an $n \times k$ matrix of explanatory variables X'_t, a $k \times 1$ vector of coefficients β_t, and an $n \times 1$ vector of innovations u_t, as follows:

$$y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix}, \quad X'_t = \begin{bmatrix} x'_{1,t} & 0_{1\times k_2} & \cdots & 0_{1\times k_n} \\ 0_{1\times k_1} & x'_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0_{1\times k_n} \\ 0_{1\times k_1} & \cdots & 0_{1\times k_{n-1}} & x'_{n,t} \end{bmatrix}, \quad \beta_t = \begin{bmatrix} \beta_{1,t} \\ \beta_{2,t} \\ \vdots \\ \beta_{n,t} \end{bmatrix}, \quad u_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{bmatrix}.$$

Then the matrix form of system (1) is given by

$$y_t = X'_t\beta_t + u_t. \tag{2}$$

The vector of innovations u_t is assumed to have a multivariate normal distribution with mean zero and covariance matrix Ω_t, i.e. $u_t \sim N(0, \Omega_t)$. This matrix can be decomposed using a triangular factorization, i.e. $A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$, where A_t and Σ_t are $n \times n$ matrices that have the following structure:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix}, \qquad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}.$$

Then, assuming that $u_t = A_t^{-1} \Sigma_t \varepsilon_t$, where ε_t is an $n \times 1$ vector whose components have independent univariate standard normal distributions, (2) can be re-written equivalently as follows:

$$y_t = X_t' \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \qquad \varepsilon_t \sim N(0, I_n). \tag{3}$$

2.2 Specification of time variation

In this section, we specify alternative sources of dynamics according to four versions of the general model described above. The first three versions include time-varying parameters, and thus allow for changes in the distributional properties of economic shocks and their propagation, but the different versions differ in the sources of time variation that they consider. The first version (labeled model A) has drifting coefficients and a "fully" time-varying covariance matrix of the observation innovations as in Primiceri (2005), permitting changes in variances and changes in the contemporaneous responses to standardized shocks (according to the lower triangular structural VAR representation considered below). Hence, this model allows to capture non-linearities and changes in the simultaneous and lagged relationships between the variables, as well as stochastic volatility in the structural shocks. The second version (model B), which follows Cogley and Sargent (2005), has drifting coefficients but only allows for changing variances. This model thus permits stochastic volatility of the shocks but the contemporaneous responses to shocks do not change over time. The third version (model C) has drifting coefficients but a fixed covariance matrix of the innovations, as in Cogley and Sargent (2002). This version rules out any changes in the variances or contemporaneous responses to shocks. In addition to the models with time-varying parameters, we also consider a version with fixed parameters (model D), where the observation innovations are the only source of time variation in the data. This model does not permit stochastic volatility, non-linearities, or other types of changes in the relationships between the variables.

Model A. This model is based on the system of observation equations (3). To complete the specification, stack the elements below the main diagonal of A_t by rows into an $n(n-1)/2 \times 1$ vector $\alpha_t = [\alpha_{21,t}, \ldots, \alpha_{n1,t}, \ldots, \alpha_{nn-1,t}]'$. Define also an $n \times 1$ vector $\omega_t = [\log \sigma_{1,t}, \ldots, \log \sigma_{n,t}]'$. With these definitions, the dynamics of the time-varying parameters are determined by the following system of state equations:

$$\beta_t = \beta_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q), \tag{4}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t, \qquad \zeta_t \sim N(0, S), \tag{5}$$

$$\omega_t = \omega_{t-1} + \eta_t, \qquad \eta_t \sim N(0, W). \tag{6}$$

The commonly applied random walk structure of the time-varying parameters in (4)-(6) is computationally convenient and, more importantly, allows various different dynamics of the parameters such as smooth shifts or abrupt jumps, and also permanent or temporary changes.

A conventional set of assumptions on the distributions of the various innovations in the observation and state equations is adopted. The covariance matrices Q and W of the vectors of state innovations ν_t and η_t are left unrestricted but the covariance matrix S of the vector of state innovations ζ_t is assumed to be block diagonal with blocks corresponding to the different rows of A_t. Furthermore, the joint distribution of the innovations is postulated as $[\varepsilon_t, \nu_t, \zeta_t, \eta_t]' \sim N(0, V_A)$, where the matrix V_A is assumed to be block diagonal with blocks I_n, Q, S, and W. These assumptions facilitate the estimation of the model and also allow to attempt a structural interpretation of the various innovations; see Primiceri (2005) and Appendix A.

Model B. This model is also based on the system of observation equations (3). The coefficients and the log standard deviations of the observation innovations are assumed to follow the processes (4) and (6), respectively, but it is assumed that

$$A_t = A, \qquad t = 1, \ldots, T.$$

The joint distribution of the innovations is postulated as $[\varepsilon_t, \nu_t, \eta_t]' \sim N(0, V_B)$, where the matrix V_B is assumed to be block diagonal with blocks I_n, Q, and W.

Model C. This model is based on the system of observation equations (2). The coefficients are assumed to follow (4) but the covariance matrix of the observation innovations is constant:

$$\Omega_t = \Omega, \qquad t = 1, \ldots, T.$$

The joint distribution of the innovations is postulated as $[u_t, \nu_t]' \sim N(0, V_C)$, where the matrix V_C is assumed to be block diagonal with blocks Ω and Q.

Model D. This model is described by the system of observation equations (2) with

$$\beta_t = \beta, \qquad \Omega_t = \Omega, \qquad t = 1, \ldots, T.$$

Under these assumptions, the system takes the form of the *seemingly unrelated regressions* model with fixed parameters as originally described by Zellner (1962).

2.3 Estimation of the models

We provide a brief description of the estimation of the above models at this stage; details are discussed in Section 3.5 and Appendix A. The estimation of the time-varying VARs follows Cogley and Sargent (2002, 2005) and Primiceri (2005) and is conducted by Bayesian Gibbs sampling methods. A Bayesian approach is appropriate in the context of time-varying VARs for two main reasons. First, as discussed by Primiceri (2005), the likelihood function of a time-varying VAR typically has peaks in multiple dimensions, some of which correspond to implausible and uninteresting regions of the parameter space that are not representative for the model's fit on a wider parameter region. The use of Bayesian methods allows to address this problem by adding probability mass to representative regions through the specification of an informative prior. Second, the computations are greatly facilitated by the use of Bayesian simulation/Gibbs sampling methods. We also use Bayesian methods to estimate the VAR with fixed parameters, in order to make the results as comparable as possible to the time-varying VAR results and to allow for straightforward marginal likelihood comparisons of this model with the other models. However, we use a very diffuse prior for this model, such that classical methods would give similar results.[5] The estimation under a Normal-Wishart prior can also be conducted by Gibbs sampling and is quite standard; see e.g. Koop (2003).

3 Empirical application

3.1 Data description

We use monthly data from December 1990 to April 2012 in the empirical application. The variables included in the data set are the average monthly JPMorgan Emerging Markets Bond Index

[5] Classical estimation of the model with fixed parameters can be conducted by iterated feasible generalized least squares (GLS), which yields consistent and asymptotically efficient maximum likelihood estimates of the parameters; see Magnus (1987).

Global (EMBIG) Performing Sovereign Spread (*spreads*), the average monthly price of refined copper at the London Metals Exchange, deflated by the U.S. Consumer Price Index for All Urban Consumers to obtain a measure in real terms and transformed into natural logarithms (*pcur*), and a monthly and seasonally adjusted indicator of total economic activity/output (IMACEC) regularly published by the Central Bank of Chile (*yr*). The EMBIG spreads are only available from December 1993 onwards; for the period December 1990-November 1993 we use instead chain-linked values of the JPMorgan EMBI+ Brady Sovereign Spread. The spreads were obtained from the Bloomberg database (series JPEGPSSD and JPSSPRD). The nominal price of copper and the IMACEC indicator are available from the SIETE database of the Central Bank of Chile (http://sieteweb.bcch.local/siete/secure/cuadros/home.aspx). The U.S. price index was obtained in seasonally adjusted form from the ALFRED database of the St. Louis Fed (http://alfred.stlouisfed.org; series CPIAUCSL). In an extension discussed below, we add the TED spread to the data set, i.e. the difference between between the interest rates for 3-month U.S. Treasury contracts (T-Bill rate, monthly averages of business days) and 3-month Eurodollars contracts according to the London Interbank Offered Rate (LIBOR, monthly averages of business days). Both interest rate series were obtained from the Bloomberg database (series US0003M Index and GB03 Govt).

3.2 Identifying restrictions on contemporaneous relations

Consider the vector of observed variables $y_t = [spreads_t, pcur_t, \triangle yr_t]'$, where $\triangle yr_t$ denotes the annual rate of change of yr_t. Following Primiceri (2005), a structural VAR model based on the system of observation equations (3) for models A and B is given by

$$y_t = X_t'\beta_t + \Xi_t\varepsilon_t, \qquad \varepsilon_t \sim N(0, I_n), \qquad t = 1, \ldots, T, \tag{7}$$

with $u_t = \Xi_t\varepsilon_t$, and where the $n \times n$ matrix Ξ_t contains at least $n(n-1)/2$ zero or cross-element restrictions, which guarantees identification. The vector ε_t then collects the identified structural shocks. The system (7) is equivalent to (3) when the matrix Ξ_t is lower triangular, such that $A_t^{-1}\Sigma_t = \Xi_t$. Hence, under a lower triangular scheme, estimation of (3) with the corresponding state equations is equivalent to direct estimation of a structural VAR with time-varying parameters, where the structural shocks have time-varying standard deviations given by the diagonal elements of the matrix Σ_t. When, on the other hand, the estimation is based on (2) as for models C and D, identification can be achieved by taking $u_t = \Xi_t\varepsilon_t$ and solving the system of equations

$$\Xi_t\Xi_t' = \Omega_t, \qquad t = 1, \ldots, T.$$

We assume in the empirical application that Ξ_t is lower triangular, and we define the relationship between the reduced-form innovations in each observation equation and the structural shocks in the following way:

$$u_t = \begin{bmatrix} u_t^{spreads} \\ u_t^{pcur} \\ u_t^{\triangle yr_t} \end{bmatrix} = \begin{bmatrix} \xi_{11,t} & 0 & 0 \\ \xi_{21,t} & \xi_{22,t} & 0 \\ \xi_{31,t} & \xi_{32,t} & \xi_{33,t} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{external\ financial\ shock} \\ \varepsilon_t^{copper\ price\ shock} \\ \varepsilon_t^{local\ shock} \end{bmatrix}.$$

External financial shocks are defined as unpredictable innovations to EMBI spreads that can have an instantaneous impact on the real price of copper and the growth rate of local economic output. The spreads are however assumed not to respond to innovations to the copper price and local economic output within a month. The latter restriction is justified by the fact that the weight of Chilean bonds in global EMBI spreads has historically been small. The first restriction is based on the implicit assumption that the risk assessment of market participants and rating agencies is not instantaneously affected by other shocks that may affect commodity prices, for instance due to learning behavior by market participants or periodic revisions of ratings conditional on past information. We make similar identifying assumptions when we add the TED spread to the model in the extension described below (see Section 4).

Copper price shocks are defined as innovations to the real price of copper that cannot be explained by external financial shocks. These are movements in the real price of copper that do not originate in the local economy, and which may capture both external demand and supply-related factors. As Chile's overall trade profile has traditionally been dependent on copper, trade-related factors should be suitably captured by such shocks (see the discussion in the introduction). The effects of oil shocks and other external factors that affect the Chilean terms of trade are also subsumed in those shocks through their impact on demand and supply for commodities, such that those shocks could also be interpreted in a wider sense as general terms of trade shocks. The real price of copper is assumed not to respond to local economic output within a month. This restriction reflects small-country features.

Local shocks are defined as innovations to the growth rate of local economic output that cannot be explained by either external financial shocks or copper price shocks. Hence, the structural VAR model postulates that all relevant external shocks that affect the Chilean economy also affect external financial spreads or the real price of copper or, equivalently, that all relevant external factors are incorporated in the spreads and the price of copper. These identifying restrictions seem to strike an acceptable balance between the reasonability of the assumed structural relations and the necessary parsimony of the empirical model.

3.3 Regression specification and cross-equation restrictions

For the above vector of observed variables y_t, the following regression specification is adopted:

$$y_t = \begin{bmatrix} spreads_t \\ pcur_t \\ \triangle yr_t \end{bmatrix} = \begin{bmatrix} x'_{1,t} & 0_5 & 0_7 \\ 0_3 & x'_{2,t} & 0_7 \\ 0_3 & 0_5 & x'_{3,t} \end{bmatrix} \begin{bmatrix} \beta_{1,t} \\ \beta_{2,t} \\ \beta_{3,t} \end{bmatrix} + u_t,$$

where

$$\begin{aligned} x_{1,t} &= [1, spreads_{t-1}, ..., spreads_{t-p,}]', \\ x_{2,t} &= [1, spreads_{t-1}, ..., spreads_{t-p}, pcur_{t-1}, ..., pcur_{t-p}]', \\ x_{3,t} &= [1, spreads_{t-1}, ..., spreads_{t-p,}, pcur_{t-1}, ..., pcur_{t-p}, \triangle yr_{t-1}, ..., \triangle yr_{t-p}]'. \end{aligned}$$

The VAR thus includes a time-varying intercept term in each equation and p lagged terms of the variables, but overidentifying cross-equation restrictions are imposed on the lagged terms. The cross-equation restrictions reflect two different exogeneity assumptions. First, external variables are assumed to be block exogenous with respect to local economic output such that past local shocks do not affect external financial spreads and the price of copper. This assumption reflects small-country features. Second, in addition to the small-country restriction, external financial spreads are assumed to be exogenous for the price of copper such that past copper price shocks do not affect the contemporaneous movements of the spreads.

Under these assumptions, overidentification strengthens the identifying restrictions made above and projects those restrictions onto lagged relationships. However, unlike the identifying restrictions, the overidentifying restrictions are testable. Marginal likelihood comparisons are a way to conduct a corresponding test. Hence, in the next section we compare estimated marginal likelihoods for the model with those restrictions against estimated marginal likelihoods for unrestricted models and models with alternative restrictions, in order to support the imposed restrictions. We also use marginal likelihood comparisons to choose the lag length. Details on the calculation of the marginal likelihoods are provided in Appendix B.

3.4 Priors

The strategy used to calibrate the priors for the time-varying VARs (models A-C) follows Primiceri (2005) and also Cogley and Sargent (2002, 2005), suitably adopted for the estimation of those models under coefficient exclusion restrictions. In particular, the priors are specified based on iterated feasible GLS results from a fixed parameters VAR estimated on an initial sample that runs from December 1990 to May 1993. The size of the initial sample (30 observations) is scaled to size of the initial sample used by Primiceri (40 observations) by the smaller number of regression parameters in our model when we use the same number of lags as in Primiceri's model (around 75%). The initial sample used to calibrate the priors is discarded for the actual estimation of models A-C. For the fixed parameters VAR (model D), which is only estimated on the actual sample, we adopt a very diffuse prior.

Model A. Let β_{GLS} denote the GLS estimates of the VAR coefficients from the initial sample and let $V(\beta_{GLS})$ denote their asymptotic covariance matrix. Further, denote the GLS estimate of the covariance matrix of the observation innovations as Ω_{GLS}. We apply a triangular decomposition to this matrix, i.e. $\Omega_{GLS} = A^{-1}_{GLS}\Sigma_{GLS}\Sigma'_{GLS}(A^{-1}_{GLS})'$, and collect the logarithms of the diagonal elements of Σ_{GLS} in the vector ω_{GLS}. The non-zero off-diagonal elements of A_{GLS}, ordered by rows, are collected in the vector α_{GLS} with asymptotic covariance matrix $V(\alpha_{GLS})$. The prior for the initial states of model A (drifting coefficients and fully time-varying covariance matrix of the observation innovations) is then specified as follows:

$$\beta_0 \sim N(\beta_{GLS}, 4 \times V(\beta_{GLS})), \tag{8}$$

$$\alpha_0 \sim N(\alpha_{GLS}, 4 \times V(\alpha_{GLS})), \tag{9}$$

$$\omega_0 \sim N(\omega_{GLS}, I_n). \tag{10}$$

This is a relatively diffuse prior for the initial states, specified as in Primiceri (2005), but which in our context is centered around the GLS estimates for the initial stretch of data. As that stretch of data is quite short, the data is only weakly informative on the initial parameters and the prior variance therefore allows for a wide range of outcomes. The priors for the covariance matrices of the state innovations take the inverse-Wishart form:

$$Q \sim IW(T_0 \times k_Q^2 \times V(\beta_{GLS}), T_0), \tag{11}$$

$$S_1 \sim IW(2 \times k_S^2 \times V(\alpha_{1,GLS}), 2), \tag{12}$$

$$S_2 \sim IW(3 \times k_S^2 \times V(\alpha_{2,GLS}), 3), \tag{13}$$

$$W \sim IW(4 \times k_W^2 \times I_n, 4), \tag{14}$$

where S_1 and S_2 stand for the two blocks of S, while $\alpha_{1,GLS}$ and $\alpha_{2,GLS}$ correspond to the blocks of α_{GLS}. The specification of those priors also follows Primiceri (2005). The degrees of freedom for the blocks of S and the matrix W are set to the dimension of each matrix plus 1, which implies that the inverse-Wishart priors are proper (i.e. they integrate to 1) but do not have finite moments (cf. Cogley and Sargent, 2005). As in Primiceri (2005), the degrees of freedom of the prior for Q are set to the size of the initial sample, i.e. $T_0 = 30$, since a slightly tighter prior is necessary to avoid implausible behaviors of the time-varying coefficients, comparable as reported by Primiceri. The factor k_Q is set to $0 \cdot 01$ and the factors k_S and k_W are both set to $0 \cdot 1$. Specified in this way, the priors are diffuse and relatively conservative in terms of the variation attributed to parameter changes, but they put somewhat more weight on changes in the covariance matrix of the observation innovations relative to coefficient changes. We have experimented with alternative choices, but our results were robust to those choices.

Model B. The prior for model B takes (8), (10), (11), and (14), together with

$$\alpha \sim N(\alpha_{GLS}, 4 \times V(\alpha_{GLS})),$$

such that the prior for the initial states α_0 from model A is projected onto α for this model.

Model C. The prior for model C takes (8) and (11), together with

$$\Omega \sim IW(\Omega_{GLS}, T_0),$$

which is comparable to the prior used in Cogley and Sargent (2002).[6]

Model D. An independent Normal-Wishart prior is adopted for model D. Thus, a normal prior is placed on the regression coefficients:

$$\beta \sim N(0_k, 4 \times I_k).$$

This prior implies that the regression coefficients are centered around points which imply that the explanatory variables have no effect on the dependent variables, but with a relatively large prior standard deviation of 2 that allows for a substantial range of outcomes.[7] Further, a Wishart prior with scale matrix $\bar{H}$ and degrees of freedom $\bar{\nu}$ is placed on the inverse of the covariance matrix of the observation innovations:

$$H \sim W(\bar{H}, \bar{\nu}).$$

[6] We experimented with an $IW(4 \times \Omega_{GLS}, T_0)$ prior for Ω, which did however not affect the results in any significant way and the estimated marginal likelihoods only changed by a few decimal points.

[7] We also experimented with a prior where β is centered on GLS estimates for the initial sample used for the time-varying VARs, i.e. $\beta \sim N(\beta_{GLS}, 4 \times V(\beta_{GLS}))$. The outcomes were hardly affected and the estimated marginal likelihoods again changed very little.

We set $\bar{H}^{-1} = 0_n$ and $\bar{\nu} = 0$ to achieve non-informativeness (see Koop, 2003).

3.5 Posterior simulations

We briefly outline the main aspects of the posterior simulations and refer to Appendix A for details on the estimation procedure. For each model that was estimated, we generated 25,000 draws using Gibbs sampling, of which we discarded the first 5,000 to let the Markov chain converge to its ergodic distribution. Of the remaining 20,000 draws, we kept every 10th draw to break the autocorrelation of the draws. This left us with 2,000 draws from the joint posterior distribution of the model parameters from which we computed statistics of interest (moments of the time-varying parameters, impulse responses, error bands, etc.).

Following Cogley and Sargent (2002) and Cogley and Sargent (2005), we imposed a reflecting barrier on the autoregressive coefficients saying that explosive draws are discarded.[8] This restriction reflects an a priori belief about the implausibility of explosive representations for external interest rate spreads, real copper prices, and local economic output in Chile. While we allow for possible stochastic volatility and also unit-root changes in the trends of those variables through a time-varying intercept term, we do not believe that those variables have explosive cyclical components. The stability restriction mainly helped to avoid explosive dynamics for the real copper price, which is also consistent with the findings of previous empirical studies on copper price dynamics; see e.g. García-Cicco and Montero (2011).

We conducted various convergence checks as discussed in more detail in Appendix A. We used the prior means of the parameters as initial values for the Markov chain, but the posterior simulator quickly added time variation in the parameters and the convergence of the chain to its ergodic distribution was quite fast. We experimented with different starting points of the Markov chain, which did however not affect our results in any significant way.

4 Estimation results

4.1 Model comparison

We begin the discussion of the estimation results by describing the outcomes of the model comparison procedure that we used to select our preferred model. In particular, we conducted a formal Bayesian comparison of the models described in the previous section, both across

[8] The reflecting barrier works as follows. The process (4) characterizes the unrestricted conditional density $f_U(\beta_t|\beta_{t-1}, Q)$. Following Cogley and Sargent (2002), introduce an indicator function $I(\beta_t)$ that rejects draws that do not satisfy standard eigenvalue stability conditions on the autoregressive coefficients and enforces non-explosiveness at each point of time. The coefficients are thus postulated to evolve as $f(\beta_t|\beta_{t-1}, Q) = I(\beta_t)f_U(\beta_t|\beta_{t-1}, Q)$. Formal results are provided in Cogley and Sargent (2005). A similar argument can be made for the Bayesian VAR with fixed parameters.

alternative models and for different specifications of individual models. Assuming that the set of specified models is exhaustive (i.e. the posterior model probabilities sum to 1), the model with the highest estimated marginal likelihood obtains the highest posterior model probability (see Koop, 2003). Model comparison is a useful step for various reasons. First, it allows to test the importance of changes in macroeconomic dynamics by testing VARs with fixed parameters against VARs with time-varying parameters. Second, it allows to test different elements of time variation in the model parameters against each other to reduce the risk of model misspecification such as omitting relevant elements and thereby falsely attributing time variation to elements that are allowed to change over time. Third, it allows to compare different specifications of the lagged relationships among the variables to address the problem of overfitting, while again reducing the risk of generating a potential bias by misspecifying the lag structure.

The estimated marginal likelihoods are reported in Table 1. The columns of the table correspond to different models and the panels and rows to different lag specifications. We now analyze the results with a particular view of the importance of time variation in the VAR parameters and different elements of parameter variation.

[Insert Table 1 here.]

Importance of heteroskedasticity. The model with drifting coefficients but a fixed covariance matrix of the observation innovations (C) obtains smaller marginal likelihoods than the model with fixed parameters (D). However, the time-varying VARs with heteroskedastic innovations (A and B) fit the data better than the fixed parameters VAR. According to these results, heteroskedasticity of the underlying shocks is a critical element of the data and may for instance be required to capture occasional spikes in EMBI spreads.[9]

Relevance of variation in simultaneous relations. Regarding variations in the contemporaneous responses to standardized shocks, which we take as the simultaneous structural relations among the variables according to (7), the results in Table 1 show that the model with a fully time-varying covariance matrix of the innovations (A) obtains the highest marginal likelihoods, in particular compared to the model with heteroskedastic innovations but fixed simultaneous structural relations (B). The differences are large, more than 100 log points on average, which

[9] As model D obtains a higher marginal likelihood than model C, one may wonder whether a model with a changing innovation covariance matrix would not be preferred over models A and B. A simple way to test this hypothesis is to estimate models A and B with a tightly restricted prior for the covariance matrix of the innovations to the coefficients (Q) that resembles such a specification. When we did this, setting $Q \sim IW(0.0000001 \times V(\beta_{GLS}), 100)$, we found that the estimated marginal likelihoods decreased for model A but increased for model B, without changing the ordering of those models.

implies that model A has a posterior model probability close to 1. Hence, changes in the simultaneous structural relations among the variables seem to be a salient feature of the data.

Testing cross-equation restrictions. The different panels of Table 1 contain marginal likelihoods for alternative cross-equation restrictions. Panel 1 corresponds to the baseline specification discussed in Section 3.3, i.e. EMBI spreads are exogenous for the remaining variables and the copper price is exogenous for local output; Panel 2 corresponds to an alternative specification–commonly used in VAR studies for small open economies–that takes external variables as block exogenous for local output but where the VAR is otherwise unrestricted; and Panel 3 corresponds to a completely unrestricted VAR. According to the estimated marginal likelihoods, the first type of specification is preferred over alternative types by a fairly large margin. We are therefore confident that the imposed cross-equation restrictions are useful to describe the data.

Testing the lag length. The different rows in the panels of Table 1 contain estimated marginal likelihoods for alternative choices of the VAR lag length, i.e. $p = 1, 2$ for each specification of cross-equation restrictions. The model with the highest marginal likelihood is model A with the regression specification discussed in Section 3.3 and $p = 1$. Hence, we select this model to proceed with the empiricial analysis.

4.2 Time-varying external volatility and propagation of shocks

This section characterizes the time-varying volatility of the external shocks based on the estimated VAR. It also describes the propagation of those shocks into external variables by analyzing time-varying impulse responses of those variables.

Measuring external volatility. We attempt to characterize the external volatility relevant for Chile through a measure in the spirit of Cogley and Sargent (2005), who suggest to measure the total amount of noise hitting a system of variables by the log determinant of the innovation covariance matrix of a time-varying VAR with stochastic volatility estimated for that system. Analogously, we define the measure $EXV_t = \frac{1}{2} \log M_{[2,2],t}$, where $M_{[2,2],t}$ is the second leading principal minor of the innovation covariance matrix Ω_t, which corresponds to the innovations to external variables. Appendix C shows that this measure has the following structural interpretation:

$$EXV_t = \log \sigma_{1,t} + \log \sigma_{2,t}, \qquad t = 1, \ldots, T,$$

such that the evolution of external volatility is completely determined by the time-varying standard deviations of the two external structural shocks.[10]

[Insert Figure 1 here.]

Figure 1 shows the median and the 16-th and 84-th percentiles of the posterior distribution of EXV_t for each month in the effective sample (i.e. June 1993 to April 2012). Several results stand out. First, the volatility of external shocks was largest in the 1990s until around 2003, a period that was characterized by several emerging market crises. Second, external volatility reached a minimum of relatively short duration during the mid-2000s. Third, the volatility of external shocks increased again from 2006 onwards towards the levels of the 1990s and early 2000s, and spikes occurred around the subprime crisis and the European debt crisis. Measured by historical standards, the average level of external volatility was relatively high since around 2007. As high volatility signals frequent shocks, large shocks or both, we may conclude that in terms of the frequency and/or the size of external shocks the recent financial crisis episodes originating in developed countries were comparable to earlier episodes.

Contribution of individual shocks. Figure 2 shows the posterior medians and 16-th and 84-th percentiles of the time-varying standard deviations of the two external shocks. The upper charts show the standard deviation of the financial shock to EMBI spreads ($\sigma_{1,t}$) and the lower charts show the standard deviation of the copper price shock ($\sigma_{2,t}$). The left-hand side charts show the standard deviations in percent while the right-hand side charts show the standard deviations in log percentages to make the scale comparable to Figure 1.

[Insert Figure 2 here.]

The upper charts in Figure 2 show that the 1990s were years of high average and quickly changing volatility of shocks to emerging market spreads, with hikes in volatility during the Mexican peso crisis in 1994-1995, the Asian financial crisis that started in July 1997 and the 1998 Russian financial crisis. However, after the peak of the Argentine crisis in late 2001, the volatility of shocks to emerging market spreads started to decline. A period of low and stable volatility followed that was almost uninterrupted from 2003 until late 2008 when the effects of the subprime financial crisis spilled over into emerging market spreads. Nevertheless, according to the point estimates, the identified financial volatility was lower than during the earlier crises, which is consistent with the fact that this crisis originated (and impacted most) in developed

[10] Appendix C also shows that EXV_t can be generalized for time-varying VARs of the form in (3).

countries. Finally, financial volatility increased mildly during the last quarter of 2011 when the European debt problems also affected emerging market spreads.

The lower charts in Figure 2 show that the volatility of copper price shocks was moderately high during 1994-1996, a period that was associated with a short boom in copper prices. After around 1996, the volatility of copper price shocks decreased towards relatively low levels during 2000-2004. After that calm period, the volatility increased rapidly with the 2005-2006 boom in commodity prices. Volatility levels remained high until the end of 2009. The volatility of copper price shocks then decreased markedly towards the levels of the early 1990s.

In summary, the volatility of both types of external shocks have shown significant changes over the sample period and periods of high volatility are assigned to well-known events. Changes in the standard deviation of shocks to EMBI spreads ($\sigma_{1,t}$) drive changes in the external volatility measure EXV_t due to their relatively large magnitude. However, the point estimate of EXV_t during the subprime financial crisis was higher than during the Argentine crisis and comparable to the level of the Mexican crisis, whereas this is not the case for $\sigma_{1,t}$. The reason is that the standard deviation of copper price shocks ($\sigma_{2,t}$) increased already before 2007, with effects on EXV_t that are observable from the right-hand side charts in Figure 2. We may therefore conclude that, while changes in external volatility in the 1990s and early 2000s were dominated by exogenous changes in the volatility of emerging market spreads, exogenous changes in copper price volatility have also had a significant role since 2005.

The results in Figure 2 are comparable to results of a related recent study by García-Cicco, Naudon, and Heresi (2012), who *inter alia* estimate the time-varying volatility of EMBI spreads and a price index for mining exports (mainly copper) based on univariate autoregressive models with stochastic volatility but fixed coefficients. The time profile of their estimated volatility of innovations to the spreads is similar to the profile of $\sigma_{1,t}$, which is explained by the fact that $\sigma_{1,t}$ is also the standard deviation of the reduced-form VAR innovations to the spreads.[11] The average profile of $\sigma_{2,t}$ is also quite similar to the estimated profile of the volatility of innovations to mining export prices of García-Cicco, Naudon, and Heresi, but with important differences in short-run dynamics. In particular, we do not find the rise in volatility reported by García-Cicco, Naudon, and Heresi in major financial crises, which may be explained by the propagation of financial shocks into copper prices; this hypothesis is explored next.

Propagation of copper price shocks. We now analyze the time-varying propagation of the two external shocks into external variables. For this purpose, we report time-varying *generalized*

[11] In addition, our model also implies a univariate specification for the spreads. The only important difference to the specification for EMBI spreads of García-Cicco, Naudon, and Heresi (2012) is that in our model time variation in the VAR coefficients competes with stochastic volatility, but our estimated variation in the coefficients is small.

impulse responses in the spirit of Koop, Pesaran, and Potter (1996) to address the uncertainty originating from future time variation in the VAR coefficients and its covariance matrix (i.e. future changes in the structure of the economy).[12] The posterior distribution of the generalized impulse responses is computed by Monte Carlo integration methods. The computation follows Benati (2008) and is described in Appendix D.

[Insert Figure 3 here.]

Figure 3 shows the median time-varying impulse responses (with 16-th and 84-th percentiles) of the real copper price to copper price shocks at selected horizons up to 36 months and for each date in the sample. The shocks are normalized to 10% at each date. Under that normalization, the shocks fall within the bands of the posterior standard deviation during the high volatility period of 2006-2009. The results show that the propagation of the shocks into the price of copper has been relatively stable over the sample period. The peak response of 13 to 14 percent occurs within half a year and then falls to around 4 to 5 percent after 36 months. At longer horizons of more than 12 months after the shock, a somewhat more persistent response is estimated for the second part of the sample, but the differences are not probabilistically significant.

Propagation of external financial shocks. Regarding the propagation of external financial shocks into EMBI spreads, Figure 4 shows that the response of the spreads to those shocks has remained almost unchanged over the sample period. The shocks are normalized to 100 basis points (b.p.) at each date, this being the order of magnitude of their volatility estimated for the last major episode, i.e. the subprime financial crisis. The estimated responses decline steadily over the horizons considered, being almost nil already 36 months after the shock.

[Insert Figure 4 here.]

However, it is interesting to note that the estimated (negative) impact of external financial shocks on the level of the real price of copper has changed significantly over the sample period. Figure 5 shows that the median response decreases notoriously from the late 1990s onwards. The impact response is close to zero for the early 1990s but close to -5 percent for the period 2008-2012. The differences are even larger at the 1-year horizon, and also at longer horizons a declining response can be noted.

[12] Generalized impulse responses take the response at horizon $t+h$ to an exogenous shock $\varepsilon_{i,t}$ to variable i at time t is defined as the difference between two conditional expectations:

$$ir_{i,t+h} = \mathrm{E}(y_{t+h}|y^{t-1}, \beta_t, \Omega_t, \varepsilon_{i,t} = \epsilon) - \mathrm{E}(y_{t+h}|y^{t-1}, \beta_t, \Omega_t), \qquad t = 1, \ldots, T, \qquad h = 0, \ldots, H,$$

where y^{t-1} is the history of observations up to time $t-1$. The first term is the forecast of y_{t+h} conditional on the current state of the economy and a shock of size ϵ. The second term is the forecast conditional on the same state but without conditioning on the shock.

[Insert Figure 5 here.]

Figure 6 further supports the statements of the previous paragraph. The upper left chart shows the trajectories of the copper price responses for four selected months. The months considered are March 1995 (identified peak contagion of the Mexican peso crisis), August 1998 (peak contagion of Asian crisis), December 2008 (peak contagion of subprime crisis), and April 2012 (last sample point). The remaining charts shows various percentiles of the differences between the impulse responses for Mar-95 and the other months. As it can be seen from the upper right chart, there are no significant differences between the Mar-95 response and the Aug-98 response. However, the differences are significant for the comparison of Mar-95 with Dec-08 and Apr-12, as it can be noted in the lower charts. The differences are significant with at least 90 percent posterior probability at horizons less than a year, but with less probability at longer horizons.

[Insert Figure 6 here.]

The larger copper price response to external financial shocks is a very important finding for the Chilean economy, an economy that is highly exposed to copper price fluctuations. This finding implies that, in present times, an unexpected tightening of external financial conditions, when measured by exogenous increases in EMBI spreads, will produce a larger fall of real copper prices in comparison to what would have happened a decade ago.

Pass-through of financial volatility into the price of copper. We show next how the larger detected response of the real price of copper to financial shocks implies a larger "pass-through" of financial volatility into copper price volatility. To do this, we split up the variance of the reduced-form copper price innovations ($u_t^{pcur} = u_{2,t}$) according to its structural components:

$$\text{var}(u_{2,t}) \quad = \quad \underbrace{(\gamma_{21,t}\sigma_{1,t})^2}_{\text{financial volatility}} \quad + \quad \underbrace{\sigma_{2,t}^2}_{\text{own volatility}}.$$

This relation is derived in Appendix C. The first term is the squared contemporaneous innovation to the price of copper due to a one-standard deviation financial shock at time t. The second term is the variance of structural shocks to the price of copper at time t. We may define the first component as the "financial"component of copper price volatility, which shows how the volatility of financial shocks ($\sigma_{1,t}^2$) is passed on through the response to such shocks ($\gamma_{21,t}^2$). The second component corresponds to autonomous or "own" structural copper price volatility.

Figure 7 shows the posterior median and the 16-th and 84-th percentiles of the financial component of var($u_{2,t}$). A significant effect can be noted during the Mexican peso crisis, the

Asian/Russian crisis, and the Argentine crisis, which are associated with hikes in the estimated $\sigma_{1,t}$ (see Figure 2). However, the financial component is much larger during the subprime crisis and the European debt crisis. As the estimated $\sigma_{1,t}$ are lower for these recent episodes compared to the earlier crises, the additional volatility is explained by the larger estimated response of the price of copper to financial shocks. Hence, the recent crises seem to have been associated with a significant pass-through of financial volatility into copper price volatility.

[Insert Figure 7 here.]

In summary, the results reported in this section show that an overall increase in financial volatility in the last couple of years has been amplified by a larger response of the price of copper to financial shocks. We may therefore conclude that the Chilean economy has become (i) more exposed to external financial shocks; and (ii) potentially more vulnerable to such shocks through their larger impact on the price of copper. In the face of this evidence, the following section explores the local transmission of external shocks in depth.

4.3 Time-varying local impact of external shocks

In this section we study the response of the Chilean economy to shocks to the price of copper and external financial conditions, focusing on the response of the growth rate of local economic output to such shocks.

Local impact of copper price shocks. We start by analyzing the local impact of copper price shocks. Figure 8 shows the evolution of the response of output growth to 10 percent copper price shocks at different time horizons. A downward trend can be observed for all horizons displayed. At shorter horizons (0, 3, 6 months), the responses decrease monotonically. At longer horizons more relevant for policy purposes (12, 24, 36 months), the estimates indicate a transition from an initial state to another. The transition seems to start around 1999-2001, a period that coincides with the years in which the monetary policy reform and the fiscal rule were officially implemented in Chile, which points towards an important impact of those reforms on the output response to copper price shocks.

[Insert Figure 8 here.]

To assess the statistical significance of the estimated changes, Figure 9 shows selected trajectories of the output growth responses and the differences between the responses in March 1995 versus August 1998, December 2008, and April 2012. The response of output growth is much lower for Dec-08 and Apr-12 than for Mar-95 and Aug-98. However, the differences for

Dec-08 and Apr-12 in comparison to Mar-95 are only significant with a posterior probability between 50 and 68 percent. Although this evidence is not very strong from a statistical point of view, the changes in point estimates are economically quite important: the average reduction in output growth is more than 1/4 percentage points. At the end of the sample, the differences reach almost 1/2 points. The differences in the impact responses are relatively unimportant; instead, the largest differences are observed at horizons of around 1 year.

[Insert Figure 9 here.]

Local impact of financial shocks. To analyze the local impact of external financial shocks, Figure 10 shows the evolution of the response of output growth to 100 b.p. shocks to the EMBI spreads for different time horizons. The charts show that the magnitude of the output responses to those shocks has also decreased over time (increased in effective values). The economic policy reforms of 1999-2001 could also be responsible for part of this effect since especially at longer horizons a state transition is estimated to have started around that time.

[Insert Figure 10 here.]

Figure 11 shows the trajectories of the responses of output growth and the differences between the responses for Mar-95 versus Aug-98, Dec-08, and Apr-12. As it can be seen, the differences are not significant at conventional probability levels. However, the point estimates are again economically important. The estimates show that 24 months after a 100 b.p. shock to EMBI spreads, up to a 1/4 percentage point decrease in output growth would have been observed in the 1990s while the change in output growth would have been close to zero in the last couple of years. It is also interesting to note that, according to the estimates reported in the previous section, external financial shocks have an *increasingly negative impact* on the price of copper in more recent years, but this change has had *no discernible impact* on the response output growth. Instead, the point estimates reported here point into the opposite direction, towards a smaller impact of external financial shocks on output growth in recent times.

[Insert Figure 11 here.]

In summary, the evolution of the output response to external shocks (to the price of copper and external financial conditions measured by emerging market spreads) shows that the Chilean economy has been relatively resilient to the higher external volatility observed during the last five years, in comparison to the 1990s and early 2000s. The most striking aspect of the results reported in this section is that, despite an increasingly negative estimated impact of a worsening of external financial conditions on price of copper, there is no stronger effect on output growth. According to our results, part of the explanation to this finding is a change in regimes around 1999-2001 that has reduced the response of the local economy particularly to copper price shocks, and that coincides with the implementation of major monetary and fiscal policy reforms in Chile.

4.4 Impact of "global" financial shocks

In this section we analyze the robustness of our main results to the use of a broader measure of external financial conditions. In particular, we analyze whether the distinction between "emerging-market-specific" financial shocks and "global" financial shocks matters for the results. Recall that the VAR discussed above uses EMBI sovereign spreads to measure changes in the external financial conditions facing the Chilean economy. We now combine the information contained in EMBI spreads with the information contained in the TED spread. By subtracting the interest rate on risk-free U.S. Treasury securities (the T-Bill rate) from the main reference rate on interbank loans (the LIBOR), the TED spread allows to measure changes in perceived credit risk in the interbank market. Since the volatility of this spread has increased significantly after 2007, the use of this variable allows to explicitly capture the tightening of financial conditions in the international financial system observed during the recent crisis. The results discussed above might be affected by adding this information to the VAR.

We add the information in the TED spread to the VAR by replacing the EMBI spreads by the first principal component of the EMBI spreads and the TED spread. The first principal component accounts for approximately 98% of the total variance of the two variables and should therefore suitably capture external financial conditions facing the Chilean economy due to both "emerging-market-specific" financial shocks and "global" financial shocks. The identifying assumptions that we make under this extension are similar to the ones discussed in Section 3. In particular, external financial shocks are now defined as unpredictable innovations to the first principal component of the EMBI spreads and the TED spread that are orthogonal to innovations to the real price of copper and the growth rate of local economic output.

[Insert Figure 12 here.]

Figure 12 shows the estimated median time-varying impulse responses to 100 b.p. external financial shocks and 10% copper price shocks according to both versions of the VAR. The outcomes show that the previous results are robust to the use of the combined measure of external financial conditions, as the estimated responses are quite close to each other. The main conclusions from our analysis are therefore not affected by the distinction between emerging-market-specific financial shocks and global financial shocks.

5 Conclusions

In this paper we have analyzed the evolution of Chile's external macroeconomic vulnerability over the past decades, with a focus on (i) the exposure to external financial shocks (measured by exogenous changes in external interest rate spreads) and copper price shocks at different points of time; and (ii) changes in the impact of such shocks on domestic output. The analysis has been based on structural small-country VARs with drifting coefficients and multivariate stochastic volatility. The results show that despite an increase in the exposure to external shocks since the mid-2000s, local output nevertheless exhibits a smaller response to external shocks than in the past in particular due to smaller estimated effects of copper price changes.

The above result is in line with previous empirical work by Franken, Fort, and Parrado (2006), who found that external shocks had historically been responsible of a significant portion of output volatility in Chile but that the effects of external shocks on output had decreased between the 1990s and the early 2000s. According to our estimations, this finding extends to the more recent period since the mid-2000s and the latest crisis episodes. Other work by Céspedes, Goldfajn, Lowe, and Valdés (2006) argues that desirable economic policies to lower the volatility of output growth are (i) a floating exchange rate, (ii) a credible inflation targeting regime, (iii) a sustainable and credible fiscal policy, and (iv) the creation of liquid and well-developed financial markets. All of these policies were implemented in Chile towards the end of the 1990s and beginning of the 2000s. According to our findings, structural changes affecting the response of output to external shocks have taken place at that time. The timing and persistence of the estimated changes suggests a particularly important role of policies (i)-(iii) in isolating the Chilean economy from external shocks, in particular to the price of copper.

An additional result of the paper is a larger estimated response of the price of copper to external financial shocks. Although other explanations are possible, this result is in line with an increasing role of commodities as financial assets over time, as emphasized by Caballero (2006) and Caballero, Farhi, and Gourinchas (2008). According to the latter, an increasing shortage of liquid financial assets since the 1980s has contributed to higher demand for commodities and helped to fuel the commodity price boom starting in the mid-2000s. However, the real economic slowdown initiated by the subprime financial crisis worked to reverse the tight commodity market conditions. The estimated (significantly) stronger reaction of the price of copper to financial conditions since the mid-2000s seems to be consistent with this explanation.

Given these findings, it would be interesting to conduct a cross-country study of time variation in the effects of external shocks for a larger set of emerging market economies or commodity-exporting countries where similar policy reforms as in Chile have been implemented over the past decades. This type of study would be useful to further investigate the role played by such reforms in isolating local economies from external shocks. It would also be interesting to complement the analysis in this paper by an analysis of changes in the effects of global financial shocks on a wider range of commodity prices (other industrial metals, oil, etc.), in order to provide a more detailed empirical assessment of the asset shortage perspective mentioned above. This type of research is left for future work.

Appendix

A Details of the estimation

This appendix provides details on the estimation of the models that were described in Section 2. We adopt the notational conventions that $v^\tau = [v_0', \ldots, v_\tau']'$ denotes the history of a generic vector v_t up to a generic time τ and that $M^\tau = [m_0', \ldots, m_\tau']'$ denotes the history of a generic matriz M_t up to generic time τ, where $m_t = \text{vec}(M_t)$ and $\text{vec}(\cdot)$ is the column stacking operator. Further, $v_-^\tau = [v_1', \ldots, v_\tau']'$ and $M_-^\tau = [m_1', \ldots, m_\tau']'$ are histories that exclude time 0 values. Finally, $f(\cdot)$ denotes a generic distribution function. The estimation is conducted by Gibbs sampling (Gelfand and Smith, 1990; Geman and Geman, 1987). We first provide a general description of Gibbs sampling before explaining the details of the estimation of each model.

Gibbs sampling

Gibbs sampling is useful to obtain a sequence of random samples from an intractable joint distribution of two or more random variables by sampling sequentially from tractable conditional distributions of individual variables.[13] The obtained sequence approximates the joint distribution. Our aim is to sample from the joint posterior of the parameters of each model, collected in θ. Gibbs sampling is based on a *blocking* scheme, i.e. a partitioning of the parameters into q different sets $\theta = \{\theta_1, \ldots, \theta_q\}$. Sampling starts with an initial sub-set $\tilde{\theta}(0) = \{\theta_2(0), ..., \theta_q(0)\}$ and the first block $\theta_1(1)$ is sampled from the conditional distribution $f(\theta_1|y^T, \tilde{\theta}(0))$ in the first iteration. The remaining blocks are then sampled sequentially from their conditional distributions. These are $f(\theta_i|y^T, \theta_1(1), ..., \theta_{i-1}(1), \theta_{i+1}(0), ..., \theta_q(0))$ for $i = 2, ..., q-1$ and $f(\theta_q|y^T, \theta_1(1), ..., \theta_{q-1}(1))$. The set of parameters obtained in the first iteration $\theta(1) = \{\theta_1(1), \ldots, \theta_q(1)\}$ is a sample from $f(\theta|y^T, \tilde{\theta}(0))$. Iterating for $j = 2, ..., M$ produces a sequence $\{\theta(j)\}_{j=1}^M$. It can be shown that, as $M \to \infty$ and under relatively mild additional conditions, the sequence $\{\theta(j)\}_{j=1}^M$ converges in distribution to the posterior $f(\theta|y^T)$ for any feasible initial set $\tilde{\theta}(0)$. To lessen the dependence on initial values, an initial sequence $\{\theta(j)\}_{j=1}^m$ is discarded from the final sequence, with $m \leq M$ but large enough. Standard convergence checks and tests can be used to ascertain whether the empirical distribution of $\theta(j)$ has converged.[14] Since the samples in $\{\theta(j)\}_{j=m+1}^M$ will generally be dependent it is also advisable to apply *thinning*, which means that only every r-th sample

[13] An *intractable* distribution is here understood to be either a distribution whose analytical form is unknown or a distribution with known analytical form that is difficult to sample from directly. Conversely, a *tractable* distribution is a distribution that has a known analytical form and that is easy to sample from directly.

[14] We used recursive mean plots and codes from James LeSage's econometrics toolbox (`http://www.spatial-econometrics.com`) to assess the convergence of the Gibbs sequence used for posterior inference.

from $\{\theta(j)\}_{j=m+1}^{M}$ is used for the inference, with r large enough.[15]

Estimation of Model A

Model A has parameters $\theta_A = \{\beta^T, \alpha^T, \omega^T, Q, S, W\}$. The observed data y^T is linked to the parameters through the likelihood function $f(y^T|\beta^T, \alpha^T, \omega^T, Q, S, W)$. Letting $f(\beta_0, \alpha_0, \omega_0, Q, S, W)$ denote a joint prior for the initial states and the covariance matrices of the state innovations, the object of interest is the joint posterior distribution of the states β^T, α^T, and ω^T and the covariance matrices Q, S, and W conditional on the observed data:

$$f(\theta_A|y^T) = \frac{f(y^T|\theta_A)f(\theta_A)}{f(y^T)} = \frac{f(y^T|\theta_A)f(\beta_-^T, \alpha_-^T, \omega_-^T|\beta_0, \alpha_0, \omega_0, Q, S, W)f(\beta_0, \alpha_0, \omega_0, Q, S, W)}{f(y^T)},$$

The Gibbs sampling algorithm that is used to approximate that joint posterior follows Primiceri (2005). A natural blocking scheme consists of the blocks β^T, α^T, ω^T, Q, S, and W. Those blocks have known individual conditional distributions given by $f(\beta^T|y^T, \alpha^T, \omega^T, Q)$, $f(\alpha^T|y^T, \beta^T, \omega^T, S)$, $f(\omega^T|y^T, \beta^T, \alpha^T, W)$, $f(Q|\beta^T)$, $f(S|\alpha^T)$, and $f(W|\omega^T)$, where conditioning variables that are redundant for the individual distributions are omitted. A complication arises because $f(\omega^T|y^T, \beta^T, \alpha^T, W)$ is intractable in the sense that exact sampling techniques cannot be used to sample ω^T. The procedure therefore takes a tractable, approximate distribution $f(\omega^T|y^T, \beta^T, \alpha^T, s^T, W)$ that depends on auxiliary parameters s^T that have themselves a tractable conditional distribution $f(s^T|y^T, \beta^T, \alpha^T, \omega^T)$. An additional block is then included for the parameters s^T. In addition, the block diagonal structure of S allows to sample from the conditional distributions $f(S_i|\alpha_i^T)$ instead of $f(S|\alpha^T)$, where $i = 1, ..., n-1$ and $\alpha_{i,t} = [\alpha_{r1,t}, \ldots, \alpha_{rn-1,t}]'$, $r = i+1$. The latter implies $n-1$ additional blocks for the S_i instead of the block for S. Accordingly, the blocks α_i^T are sampled from $f(\alpha_i^T|y^T, \beta^T, \omega^T, S_i)$.

The joint prior is then given by $f(\beta_0, \alpha_0, \omega_0, Q, S_1, ..., S_{n-1}, W)$. It is convenient to use an independent Normal-Wishart prior, i.e. normal for β_0, α_0, and ω_0, and inverse-Wishart for Q, W, and the S_i, $i = 1, ..., n-1$.[16] Thus, the joint prior is specified as

$$f(\beta_0, \alpha_0, \omega_0, Q, S_1, ..., S_{n-1}, W) = f(\beta_0)f(\alpha_0)f(\omega_0)f(Q)f(S_1) \times \cdots \times f(S_{n-1})f(W),$$

where the marginal priors are specified as described in Section 3.4. In particular, the prior means and variances for the normal distributions of β_0, α_0, and ω_0 and the scale matrices

[15] See Casella and George (1992) for a discussion of several of those points and further references. For a detailed discussion of the Gibbs sampler in a Bayesian context, see e.g. Geweke (1999).

[16] This type of prior is convenient because it is the natural conjugate prior in a time-varying VAR model as the one considered, i.e. the posterior of β^T, α^T, and ω^T is normal, by linearity of the state equations and normality of the state innovations, and the posterior of Q, W, and the S_i is of the inverse-Wishart form.

for the inverse-Wishart distributions Q, W, and the S_i are calibrated based on maximum-likelihood estimates for an initial sample of observations.[17] The algorithm then consists of the following steps to generate the desired sequence of random samples from the joint posterior $f(\beta^T, \alpha^T, \omega^T, Q, S_1, ..., S_{n-1}, W|y^T)$.

Initialization of α^T, ω^T, Q, S_i, $i = 1, ..., n-1$, and W. The individual blocks are initialized by their respective prior means. Other starting points could be used but, after convergence, the final sequence of random samples will be independent of the initial conditions.

Sampling from $f(\beta^T|y^T, \alpha^T, \omega^T, Q)$. Given α^T and ω^T, we obtain a history Ω^T. Conditional on y^T, Ω^T, and Q, and by linearity of the equations and normality of the marginal prior $f(\beta_0)$ and the respective innovations, the system of equations (3) and (4) has a linear Gaussian state-space form, which allows to use the Kalman filter and a backward recursion to sample from $f(\beta^T|y^T, \alpha^T, \omega^T, Q)$. The conditional posterior distribution of β^T is factored as follows:

$$f(\beta^T|y^T, \Omega^T, Q) = f(\beta_T|y^T, \Omega^T, Q) \prod_{t=0}^{T-1} f(\beta_t|\beta_{t+1}, y^T, \Omega^T, Q), \tag{15}$$

where the individual conditional distributions are given by

$$\beta_T|y^T, \Omega^T, Q \sim N(\beta_{T|T}, P_{T|T}), \qquad \beta_t|\beta_{t+1,}y^T, \Omega^T, Q \sim N(\beta_{t|t+1,}P_{t|t+1}),$$

with means and variances

$$\beta_{t|t+1} = \mathrm{E}(\beta_t|\beta_{t+1}, y^T, \Omega^T, Q), \qquad P_{t|t+1} = \mathrm{var}(P_t|P_{t+1}, y^T, \Omega^T, Q).$$

The means and variances are computed using a standard Kalman filter and simulation smoother described by Carter and Kohn (1994); see also Cogley and Sargent (2005) and Primiceri (2005). As the prediction $\beta_{t|t-1}$ is equal to $\beta_{t-1|t-1}$ under (4), the Kalman filter recursions are given by

$$\begin{aligned} P_{t|t-1} &= P_{t-1|t-1} + Q, & K_t &= P_{t|t-1}X_t(X_t'P_{t|t-1}X_t + \Omega_t)^{-1}, \\ \beta_{t|t} &= \beta_{t-1|t-1} + K_t(y_t - X_t'\beta_{t-1|t-1}), & P_{t|t} &= P_{t|t-1} - K_tX_t'P_{t|t-1}. \end{aligned}$$

The initial point $\beta_{0|0}$ for this recursion is the mean of the prior $f(\beta_0)$, and $P_{0|0}$ is the variance of $f(\beta_0)$. The Kalman filter delivers as its last point $\beta_{T|T}$ with $P_{T|T}$. Samples from (15) are then obtained by a backward recursion. The first point β_T in the backward recursion is a sample

[17] Exact asymptotic results are available for this purpose (see Hamilton, 1994, chap. 11).

from $N(\beta_{T|T}, P_{T|T})$. The remaining points β_t, $t = T-1, ..., 0$, are samples from $N(\beta_{t|t+1}, P_{t|t+1})$, where the means and variances are calculated recursively as follows:

$$\beta_{t|t+1} = \beta_{t|t} + P_{t|t}P^{-1}_{t+1|t}(\beta_{t+1} - \beta_{t|t}), \qquad P_{t|t+1} = P_{t|t} - P_{t|t}P^{-1}_{t+1|t}P_{t|t}.$$

Sampling from $f(\alpha_i^T|y^T, \beta^T, \omega^T, S_i)$, $i = 1, \dots, n-1$. Given ω^T, we obtain a history Σ^T, allowing to re-write the system of equations (3) as follows:

$$A_t\widehat{y}_t = \Sigma_t\varepsilon_t, \tag{16}$$

where $\widehat{y}_t = y_t - X_t'\beta_t$ is observable given y^T and β^T. The matrix A_t is lower triangular with ones on the main diagonal such that, recalling the definition of α_t, we can write

$$\widehat{y}_t = Z_t\alpha_t + \Sigma_t\varepsilon_t. \tag{17}$$

The $n \times n(n-1)/2$ matrix Z_t has the following structure:

$$Z_t = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ -\widehat{y}_{1,t} & 0 & \cdots & 0 \\ 0 & [-\widehat{y}_{1,t}, -\widehat{y}_{2,t}] & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & [-\widehat{y}_{1,t}, \dots, -\widehat{y}_{n-1,t}] \end{bmatrix}.$$

By normality of the marginal prior $f(\alpha_0)$ and the innovations, the system of equations (17) together with (5) has a Gaussian but non-linear state-space form. However, as suggested by Primiceri (2005), under block diagonality of S the problem becomes linear because the individual equations in (17) are then independent. Hence, the algorithm of Carter and Kohn (1994) can be applied equation by equation to sample α^T from

$$\alpha_{i,T}|y^T, \beta^T, \Sigma^T, S_i \sim N(\alpha_{i,T|T}, \Lambda_{i,T|T}), \qquad \alpha_{i,t}|\alpha_{i,t+1}, y^t, \beta^T, \Sigma^T, S_i \sim N(\alpha_{i,t|t+1}, \Lambda_{i,t|t+1}),$$

for $i = 1, \dots, n-1$, where $\alpha_{i,t}$ is the block of α_t corresponding to the $(i+1)$-th equation in (17) and S_i is the associated block of S. The means $\alpha_{i,T|T}$ and $\alpha_{i,t|t+1}$ and the variances $\Lambda_{i,T|T}$ and $\Lambda_{i,t|t+1}$ are calculated similarly as in the previous step.

Sampling from $f(\omega^T|y^T, \beta^T, \alpha^T, s^T, W)$**.** Given y^T, β^T, and α^T, we can write

$$\tilde{y}_t = \Sigma_t \varepsilon_t,$$

where $\tilde{y}_t = A_t(y_t - X_t'\beta_t)$. By diagonality of Σ_t, taking logs of the squares of both sides yields

$$\log(\tilde{y}_{h,t}^2) = 2\log\sigma_{h,t} + \log(\varepsilon_{h,t}^2), \qquad h = 1, \ldots, n.$$

The evolution of ω_t is then also characterized by a state-space model, and samples of ω^T can be obtained by a stochastic volatility algorithm described by Kim, Shephard, and Chib (1998). Define $y_{h,t}^* = \log(\tilde{y}_{h,t}^2 + c)$, $\omega_{h,t} = \log\sigma_{h,t}$, and $e_{h,t} = \log(\varepsilon_{h,t}^2)$. The value c is an *offset constant* (set to $0 \cdot 001$) whose purpose is to improve the numerical robustness of the algorithm when $\tilde{y}_{h,t}^2$ becomes very small. Stack the individual elements $y_{h,t}^*$, $\omega_{h,t}$, and $e_{h,t}$ in the $n \times 1$ vectors y_t^*, ω_t, and e_t. The state-space model is then formed by the system of observation equations

$$y_t^* = 2\omega_t + e_t, \tag{18}$$

and the state equations (6). This model is linear but not Gaussian because the individual disturbance terms $e_{h,t}$, being logs of the squares of the standard normal random variables $\varepsilon_{h,t}$, are distributed as $\log\chi^2(1)$. Thus, y_t^* has a non-Gaussian distribution, which implies that the evolution of ω_t is intractable in the sense that exact techniques cannot be used to sample ω^T. To obtain a tractable representation of the evolution of ω_t, Kim, Shephard, and Chib (1998) suggest to approximate the $\log\chi^2$ distribution by a mixture of seven normal distributions with component probabilities q_j, means $m_j - 1 \cdot 2704$, and variances v_j^2, $j = 1, ..., 7$.[18] Define as $s^T = [s_1, ..., s_T]'$ an $n \times T$ matrix of indicator variables, whose elements $s_{i,t}$ can take values from 1 to 7 and indicate which of the seven normal distributions is active in period t for each disturbance term $e_{i,t}$. The mixture of normals approximation assumes that

$$e_{h,t}|s_{h,t} = j \sim N(m_j, v_j^2), \qquad \Pr(s_{h,t} = j) = q_j, \qquad h = 1, ..., n, \qquad j = 1, ..., 7.$$

Conditional on y^T, β^T, α^T, W, and s^T, and by normality of the marginal prior $f(\omega_0)$ and the innovations, the system formed by (18) and (6) now has an approximate linear Gaussian state-space form, and we use the algorithm of Carter and Kohn (1994) to sample from

$$\omega_T|y^T, \beta^T, \alpha^T, s^T, W \sim N(\omega_{T|T}, \Upsilon_{T|T}), \qquad \omega_t|\omega_{t+1}, y^t, \beta^T, \alpha^T, s^T, W \sim N(\omega_{t|t+1}, \Upsilon_{t|t+1}),$$

[18] Kim, Shephard, and Chib (1998) choose these values for q_j, m_j and v_j^2 to make the mixture approximation for the density $\log\chi^2(1)$ sufficiently good. Notice that the mean of the $\log\chi^2(1)$ distribution is equal to $-1 \cdot 2704$.

where the means $\omega_{T|T}$ and $\omega_{t|t+1}$ and the variances $\Upsilon_{T|T}$ and $\Upsilon_{t|t+1}$ are calculated similarly as in the previous steps.

Sampling from $f(s^T|y^T,\beta^T,\alpha^T,\omega^T)$. Given y^T, β^T, α^T, and ω^T, the indicator variables in s^T are sampled from the discrete density defined by

$$\Pr(s_{h,t}=j|y^*_{h,t},\omega_{h,t}) \propto q_j f_N(y^*_{h,t}|2\omega_{h,t}+m_j-1\cdot 2704, v_j^2), \qquad h=1,...,n, \qquad j=1,...,7,$$

where $f_N(\cdot)$ denotes the normal density function (see Kim, Shephard, and Chib, 1998).

Sampling from $f(Q|\beta^T)$, $f(W|\omega^T)$, and $f(S_i|\alpha^T)$, $i=1,\ldots,n-1$. Conditional on β^T, ω^T, and α^T, respectively, samples of Q, W, and the $n-1$ blocks of S are obtained using the following standard procedure (see e.g. Gelman, Carlin, Stern, and Rubin, 2003). Consider a generic $w\times 1$ vector v_t that is distributed as $N(0,R)$, and assume an inverse-Wishart prior for R with scale matrix $\underline{R}$ and degrees of freedom $\underline{r}$, i.e. $R\sim IW(\underline{R},\underline{r})$. If we have T observations grouped in the $w\times T$ matrix $V^T=[v_1,...,v_T]$, then the conditional posterior of R is given by

$$R|V^T\sim IW(\bar{R},\bar{r}), \qquad \bar{R}=\underline{R}+V^TV^{T\prime}, \qquad \bar{r}=\underline{r}+T.$$

Therefore, using respectively $v_t=\beta_t-\beta_{t-1}$, $v_t=\omega_t-\omega_{t-1}$, and $v_t=\alpha_{i,t}-\alpha_{i,t-1}$, $i=1,\ldots,n-1$, for the cases of Q, W, and S_j, we can sample each of these matrices as follows. Conditional on V^T, the inverse of R has a Wishart distribution with scale matrix $\bar{R}^{-1}$ and degrees of freedom $\bar{r}$. Therefore, we first sample a random matrix from $W(\bar{R}^{-1},\bar{r})$ and obtain a random matrix from $IW(\bar{R},\bar{r})$ by taking the inverse of that matrix. The random matrix from $W(\bar{R}^{-1},\bar{r})$ is obtained by sampling w random vectors a_l, $l=1,\ldots,w$, each of which has size $\bar{r}\times 1$, from a multivariate normal distribution with mean zero and variance $\bar{R}^{-1}$. Then one forms the matrix $A=[a_1,\ldots,a_w]$ and calculates $(A'A)^{-1}$, which has the desired inverse-Wishart distribution.

Algorithm model A. In summary, the Gibbs sampling algorithm for model A consists of the following steps:

1. Initialize α^T, ω^T, Q, S, and W.
2. Sample β^T from $f(\beta^T|y^T,\alpha^T,\omega^T,Q)$.
3. Sample α_i^T from $f(\alpha_i^T|y^T,\beta^T,\omega^T,S_i)$, for $i=1,\ldots,n-1$.
4. Sample ω^T from $f(\omega^T|y^T,\beta^T,\alpha^T,s^T,W)$.

5. Sample s^T from $f(s^T|y^T, \alpha^T, \omega^T)$.

6. Sample Q from $f(Q|y^T, \beta^T)$, sample W from $f(W|y^T, \omega^T)$, and sample S_i from $f(S_i|y^T, \alpha_i^T)$, for $i = 1, \ldots, n-1$.

7. Go to step 2.

Estimation of Model B

Model B has parameters $\theta_B = \{\beta^T, \alpha^T, \omega^T, Q, W\}$ with $\alpha^T = \alpha$ for $t = 0, ..., T$. The individual blocks have conditional distributions given by $f(\beta^T|y^T, \alpha, \omega^T, Q)$, $f(\alpha|y^T, \beta^T, \omega^T)$, $f(\omega^T|y^T, \beta^T, \alpha, W)$, $f(Q|\beta^T)$, and $f(W|\omega^T)$. The estimation procedure again takes an additional block s^T with $f(s^T|y^T, \beta^T, \alpha, \omega^T)$ and uses $f(\omega^T|y^T, \beta^T, \alpha, s^T, W)$. The joint prior for the initial states, the α, and the covariance matrices of the state innovations is then given by $f(\beta_0, \alpha, \omega_0, Q, W) = f(\beta_0)f(\alpha)f(\omega_0)f(Q)f(W)$, where the marginal priors are specified as described in Section 3.4.

Algorithm model B. The Gibbs sampling algorithm for model B is as follows:

1. Initialize α, ω^T, Q, S, and W.

2. Sample β^T from $f(\beta^T|y^T, \alpha, \omega^T, Q)$.

3. Sample α_i from $f(\alpha_i|y^T, \beta^T, \omega^T)$, for $i = 1, \ldots, n-1$.

4. Sample ω^T from $f(\omega^T|y^T, \beta^T, \alpha, s^T, W)$.

5. Sample s^T from $f(s^T|y^T, \alpha, \omega^T)$.

6. Sample Q from $f(Q|y^T, \beta^T)$ and sample W from $f(W|y^T, \omega^T)$.

7. Go to step 2.

Steps 1-2 and 4-6 are identical to the steps described for model A, replacing α_t by α for $t = 1, ..., T$. Step 3 follows Cogley and Sargent (2005).

Sampling from $f(\alpha_i|y^T, \beta^T, \omega^T)$, $i = 1, \ldots, n-1$. Given y^T, β^T, and ω^T, the system (17) can be expressed as a system of *seemingly unrelated regressions* with standard normal residuals:

$$\breve{y}_t = \breve{Z}_t \alpha + \varepsilon_t, \tag{19}$$

where $\breve{y}_t = [\sigma_{1,t}^{-1}\widehat{y}_{1,t}, \ldots, \sigma_{n,t}^{-1}\widehat{y}_{n,t}]'$ and

$$\breve{Z}_t = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ -\sigma_{2,t}^{-1}\widehat{y}_{1,t} & 0 & \cdots & 0 \\ 0 & [-\sigma_{3,t}^{-1}\widehat{y}_{1,t}, -\sigma_{3,t}^{-1}\widehat{y}_{2,t}] & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & [-\sigma_{n,t}^{-1}\widehat{y}_{1,t}, \ldots, -\sigma_{n,t}^{-1}\widehat{y}_{n-1,t}] \end{bmatrix}.$$

The prior for the regression coefficients is specified as follows:

$$\alpha_i \sim N(\underline{\alpha}_i, \underline{V}_i), \qquad i = 1, \ldots, n-1$$

where α_i is the block of α corresponding to the $(i+1)$-th equation in (19). Then, given the *seemingly unrelated regressions* form, the posterior is given by

$$\alpha_i | y^T, \beta^T, \omega^T \sim N(\bar{\alpha}_i, \bar{V}_i), \tag{20}$$

with means and variances

$$\bar{V}_i = (\underline{V}_i^{-1} + \breve{Z}_i'\breve{Z}_i)^{-1}, \qquad \bar{\alpha}_i = \bar{V}_i(\underline{V}_i^{-1}\underline{\alpha}_i + \breve{Z}_i'\breve{y}_i),$$

where

$$\breve{y}_i = \begin{bmatrix} -\sigma_{i+1,1}^{-1}\widehat{y}_{i+1,1} \\ \vdots \\ -\sigma_{i+1,T}^{-1}\widehat{y}_{i+1,T} \end{bmatrix}, \qquad \breve{Z}_i = \begin{bmatrix} -\sigma_{i+1,1}^{-1}\widehat{y}_{1,1} & \cdots & -\sigma_{i+1,1}^{-1}\widehat{y}_{i,1} \\ \vdots & \ddots & \vdots \\ -\sigma_{i+1,T}^{-1}\widehat{y}_{1,T} & \cdots & -\sigma_{i+1,T}^{-1}\widehat{y}_{i,T} \end{bmatrix}$$

collect the variables corresponding the $(i+1)$-th equation. With these transformations, the $n-1$ blocks of α can be sampled from (20).

Estimation of Model C

Model C has parameters $\theta_C = \{\beta^T, \Omega^T, Q\}$, with $\Omega_t = \Omega$ for $t = 0, ..., T$. The individual blocks have conditional distributions given by $f(\beta^T | y^T, \Omega, Q)$, $f(\Omega | y^T, \beta^T)$, and $f(Q|\beta^T)$. The joint prior for the initial states, Ω, and Q is then given by $f(\beta_0, \Omega, Q) = f(\beta_0)f(\Omega)f(Q)$, where the marginal priors are specified as described in Section 3.4.

Algorithm model C. The Gibbs sampling algorithm for model C is as follows:

1. Initialize Ω and Q.

2. Sample β^T from $f(\beta^T|y^T, \Omega, Q)$.

3. Sample Ω from $f(\Omega|y^T, \beta^T)$.

4. Sample Q from $f(Q|y^T, \beta^T)$.

5. Go to step 2.

Steps 1-2 and 4 are identical to the steps described for model A, replacing Ω_t by Ω for $t = 1, ..., T$. Step 3 follows Cogley and Sargent (2002), modified to take into account independence of the VAR innovations and the state innovations, which is assumed in models A-C and also in Cogley and Sargent (2005) and Primiceri (2005) but not in Cogley and Sargent (2002).

Sampling from $f(\Omega|y^T, \beta^T)$. Under an inverse-Wishart marginal prior for Ω with scale matrix $\underline{\Omega}$ and degrees of freedom $\underline{r}$, the conditional posterior distribution of Ω is given by

$$\Omega|y^T, \beta^T \sim IW(\bar{R}, \bar{r}), \qquad \bar{R} = \underline{\Omega} + \hat{Y}^T \hat{Y}^{T\prime}, \qquad \bar{r} = \underline{r} + T,$$

with $\hat{Y}^T = [\widehat{y}_1, \ldots, \widehat{y}_T]$. Samples from this distribution can be obtained by the same procedure as used to sample from $f(Q|\beta^T)$; see the discussion for model A.

Estimation of Model D

The estimation of model D (the *seemingly unrelated regressions* model with fixed parameters) under an independent Normal-Wishart prior is standard textbook material and is therefore only briefly discussed here.

Algorithm model C. The associated Gibbs sampling algorithm is as follows:

1. Initialize Ω.

2. Sample β from $f(\beta^T|y^T, \Omega)$.

3. Sample Ω from $f(\Omega|y^T, \beta^T)$.

4. Go to step 2.

See, for instance, Koop (2003, chapter 6) for further details.

B Calculation of marginal likelihoods

This appendix describes the calculation of the marginal likelihoods reported in the main text. The calculation is based on Newton and Raftery (1994). Throughout, θ_X collects the parameters of a specific model x with the joint likelihood function $f_X(y^T|\theta_X)$ and a joint prior distribution for the parameters $f(\theta_X)$; for instance, model A has $\theta_A = \{\beta^T, \alpha^T, \omega^T, Q, S, W\}$. The calculation of the marginal likelihoods requires likelihood evaluations that are conducted as follows. Conditional on the matrices Ω_t (or Ω) and Q, models A-C have a normal linear state space representation

$$
\begin{aligned}
y_t &= X_t'\beta_t + u_t, && u_t \sim N(0, \Omega_t), \\
\beta_t &= \beta_{t-1} + \nu_t, && \nu_t \sim N(0, Q), \qquad t = 1, \ldots, T,
\end{aligned}
$$

with $\beta_0 \sim N(\bar{\beta}, \bar{P}_\beta)$. With $x \in \{A, B, C\}$, the log likelihood satisfies

$$
\log f(y^T|\theta_X) = \log f(y_1|\theta_X) + \textstyle\sum_{t=2}^T \log f(y_t|y^{t-1}, \theta_X),
$$

and

$$
y_t|y^{t-1}, \theta_X \sim N(X_t'\beta_{t|t-1}, X_t'P_{t|t-1}X_t + \Omega_t), \qquad t = 2, \ldots, T,
$$

and $y_1|\theta_X \sim N(X_1'\beta_{1|0}, X_1'P_{1|0}X_1 + \Omega_1)$, where $\beta_{t|t-1}$ and $P_{t|t-1}$ are calculated from the Kalman filter recursions:

$$
\begin{aligned}
\beta_{t|t-1} &= \beta_{t-1|t-1}, \\
P_{t|t-1} &= P_{t-1|t-1} + Q, \\
K_t &= P_{t|t-1}X_t(X_t'P_{t|t-1}X_t + \Omega_t)^{-1}, \\
\beta_{t|t} &= \beta_{t|t-1} + K_t(y_t - X_t'\beta_{t|t-1}), \\
P_{t|t} &= P_{t|t-1} - K_tX_t'P_{t|t-1},
\end{aligned}
$$

starting at $\beta_{0|0} = \bar{\beta}$ and $P_{0|0} = \bar{P}_\beta$. The log likelihood is then given by

$$
\begin{aligned}
\log f(y^T|\theta_X) &= -\frac{Tn}{2}\log 2\pi - \frac{1}{2}\textstyle\sum_{t=1}^T \log\left|X_t'P_{t|t-1}X_t + \Omega_t\right| \\
&\quad -\frac{1}{2}\textstyle\sum_{t=1}^T (y_t - X_t'\beta_{t|t-1})'(X_t'P_{t|t-1}X_t + \Omega_t)^{-1}(y_t - X_t'\beta_{t|t-1}).
\end{aligned}
$$

The log likelihood of the fixed-parameters model D is given by

$$\log f(y^T|\theta_D) = -\frac{Tn}{2}(1+\log 2\pi) - \frac{T}{2}\log|\Omega|\,.$$

An estimator of the marginal likelihood for model x, i.e. $f_X(y^T) = \int f_X(y^T|\theta_X) f(\theta_X) d\theta_X$, is then given by the harmonic mean of the sampled likelihood values, as described by Newton and Raftery (1994): An importance sampling method for evaluating the integral $\int f_X(y^T|\theta_X) f(\theta_X) d\theta_X$ is to generate a sample $\{\theta_X(j)\}_{j=1}^N$ from an importance function $f^*(\theta_X)$. In particular, since $\int f(\theta_X) d\theta_X = 1$ we can write

$$f_X(y^T) = \frac{\int [f(\theta_X)/f^*(\theta_X)] f_X(y^T|\theta_X) f^*(\theta_X) d\theta_X}{\int [f(\theta_X)/f^*(\theta_X)] f^*(\theta_X) d\theta_X},$$

such that an importance sampling based estimate of $f_X(y^T)$ is given by

$$\hat{f}_X(y^T) = \frac{\sum_{j=1}^N w(j) f_X(y^T|\theta_X(j))}{\sum_{j=1}^M w(j)}, \qquad (21)$$

where $w(j) = f(\theta_X(j))/f^*(\theta_X(j))$ are the importance weights. Let $\{\theta_X(j)\}_{j=1}^N$ be a sample from the posterior density $f_X(\theta_X|y^T) = f_X(y^T|\theta_X) f(\theta_X)/f_X(y^T)$. As suggested by Newton and Raftery (1994), the posterior $f_X(\theta_X|y^T)$ is well suited as an importance function for the prior $f(\theta_X)$. Thus, using $f^*(\theta_X) = f_X(\theta_X|y^T)$ in (21) yields the harmonic mean estimator of $f_X(y^T)$ based on the sample $\{\theta_X(j)\}_{j=1}^N$:

$$\hat{f}_X^{hm}(y^T) = \left[\frac{1}{N}\sum_{j=1}^N \frac{1}{f_X(y^T|\theta_X(j))}\right]^{-1}, \qquad (22)$$

which converges almost surely to $f_X(y^T)$ as $N \to \infty$ under weak conditions.[19] It is convenient from a numerical point of view to calculate the log marginal likelihood $\log \hat{f}_X^{hm}(y^T)$ from the sampled log likelihood values $\log f_X(y^T|\theta_X(j))$, as follows:

$$\log \hat{f}_X^{hm}(y^T) = \log N - \kappa - \log \sum_{j=1}^N \exp[-\log f_X(y^T|\theta_X(j)) - \kappa],$$

where the constant $\kappa = \max_j[-\log f_X(y^T|\theta_X(j))]$ is added/subtracted for numerical stability.

[19] The relevant conditions are that the support of $f^*(\theta_x)$ includes the support of $f(\theta_x)$, which is the case when $f^*(\theta_x) = f_x(\theta_x|y^T)$, and that $f_x(y^T)$ exists. See Geweke (1989) for a proof.

C Derivation of external volatility measure

In this appendix, we provide a derivation of the external volatility measure that was defined in Section 4 for model A. Consider first the 3-variate case. Take the triangular decomposition $A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$ for that case and define a 3×3 matrix Γ_t as follows:

$$\Gamma_t = A_t^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ \gamma_{21,t} & 1 & 0 \\ \gamma_{31,t} & \gamma_{32,t} & 1 \end{bmatrix}, \qquad t = 1, \ldots, T.$$

The parameters of Γ_t are linked to the parameters of A_t through the relations

$$\gamma_{21,t} = -\alpha_{21,t}, \qquad \gamma_{33,t} = \alpha_{21,t}\alpha_{32,t} - \alpha_{31,t}, \qquad \gamma_{32,t} = -\alpha_{32,t}.$$

Thus, the matrix Ω_t is equivalently defined as

$$\Omega_t = \Gamma_t \Sigma_t \Sigma_t' \Gamma_t' = \begin{bmatrix} \sigma_{1,t}^2 & \gamma_{21,t}\sigma_{1,t}^2 & \gamma_{31,t}\sigma_{1,t}^2 \\ \gamma_{21,t}\sigma_{1,t}^2 & \gamma_{21,t}^2\sigma_{1,t}^2 + \sigma_{2,t}^2 & \gamma_{21,t}\gamma_{31,t}\sigma_{1,t}^2 + \gamma_{32,t}\sigma_{2,t}^2 \\ \gamma_{31,t}\sigma_{1,t}^2 & \gamma_{21,t}\gamma_{31,t}\sigma_{1,t}^2 + \gamma_{32,t}\sigma_{2,t}^2 & \gamma_{31,t}^2\sigma_{1,t}^2 + \gamma_{32,t}^2\sigma_{2,t}^2 + \sigma_{3,t}^2 \end{bmatrix}. \qquad (23)$$

Now define as $M_{[2,2],t}$ the determinant of the upper left 2×2 block of Ω_t, or the second leading principal minor of Ω_t. Taking the natural logarithm of $M_{[2\times 2],t}$ and multiplying by $\frac{1}{2}$ yields

$$\frac{1}{2} \log M_{[2,2],t} = \log \sigma_{1,t} + \log \sigma_{2,t}.$$

Hence, the log of the first leading principal minor of Ω_t is equal to the sum of the log standard deviations of the first two structural shocks. This result generalizes to n-variate (time-varying) VARs of the form (3) under a lower triangular identification scheme. That is, $\frac{1}{2}$ times the log of the k-th leading principal minors of the innovation covariance matrix is equal to the sum of the log standard deviations of the first k structural shocks:

$$\frac{1}{2} \log M_{[k,k],t} = \sum_{k=1}^{i} \log \sigma_{k,t}, \qquad i = 1, \ldots, n.$$

The external volatility measure is defined as $EXV_t = \frac{1}{2} \log M_{[j,j],t}$, ordering the j external variables first in the VAR.

D Computation of generalized impulse responses

This appendix describes the Monte Carlo integration procedure that is used to compute the generalized impulse responses reported in Section 4. The implementation follows Benati (2008) under some minor modifications. We consider a structural shock $\varepsilon_{i,t}$ of size ϵ for model A. The following procedure is performed for $f = 1, \ldots, F$ and $t = 1, \ldots, T$:

1. Draw the current structure of the economy β_t and Ω_t from the posterior.

2. Given β_t and Ω_t, repeat the following steps for $g = 1, \ldots, G$:

   (a) Draw n independent standard normal variables, the structural shocks ε_t.

   (b) Based on $\Xi_t \Xi_t' = \Omega_t$, compute the reduced-form innovations $u_t = \Xi_t \varepsilon_t$.

   (c) Based on the state equations (4)-(6), simulate sequences $\left\{\beta_{t+h}\right\}_{h=1}^{H}$ and $\{\Omega_{t+h}\}_{h=1}^{H}$.

   (d) Based on the sequence $\{\Omega_{t+h}\}_{h=1}^{H}$, draw a sequence $\{u_{t+h}\}_{h=1}^{H}$.

   (e) Based on the system of observation equations (2) and the sequences $\{u_{t+h}\}_{h=0}^{H}$ and $\left\{\beta_{t+h}\right\}_{h=1}^{H}$, simulate a sequence of observations $\{y_{t+h}\}_{h=0}^{H}$.

3. Call the obtained simulated paths of observed variables $\{\dot{y}_{t+h}(g)\}_{h=0}^{H}$.

4. Simulate G additional paths of observed variables as in step 2 based on the same $\{u_{t+h}\}_{h=1}^{H}$, the same $\left\{\beta_{t+h}\right\}_{h=1}^{H}$ and the same Ξ_t, but replace the reduced-form innovations at time t using as structural shocks $\varepsilon_t + \iota_i$, where ι_i is an $n \times 1$ vector whose i-th element is equal to ϵ and whose remaining elements are 0.

5. Denote the simulated paths obtained in step 4 as $\{\ddot{y}_{t+h}(g)\}_{h=0}^{H}$.

6. Compute $ir_{i,t+h}(f) = \frac{1}{G}\sum_{g=1}^{G}(\ddot{y}_{t+h}(g) - \dot{y}_{t+h}(g))$ for $h = 0, \ldots, H$.

Each $ir_{i,t+h}(f)$ is a sample from the posterior distribution of generalized impulse responses. We use $F = 1,000$ posterior draws of β_t and Ω_t and generate $G = 100$ simulated paths of observed variables for each draw. These values of F and G are the same as used by Benati (2008). The impulse response horizon is set to $H = 36$ months.

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Table 1: Marginal model likelihoods.

	Model A Drifting coefficients, time-vary. cov. matrix	**Model B** Drifting coefficients, time-varying variances	**Model C** Drifting coefficients, fixed covar. matrix	**Model D** Fixed coefficients, fixed covar. matrix
Panel 1: Bond spreads exogenous, price of copper exogenous for local output (baseline)				
Lag 1	280.1	176.6	110.2	126.4
Lag 2	278.2	136.3	124.3	151.8
Panel 2: Bond spreads and price of copper block exogenous for local output				
Lag 1	273.6	173.6	106.4	129.5
Lag 2	223.2	117.7	118.8	150.2
Panel 3: Unrestricted VAR				
Lag 1	268.7	153.3	103.6	128.6
Lag 2	264.5	134.9	114.7	148.2

Note: The table entries are harmonic mean estimates of marginal model likelihoods; see Appendix B for a description of the estimation.

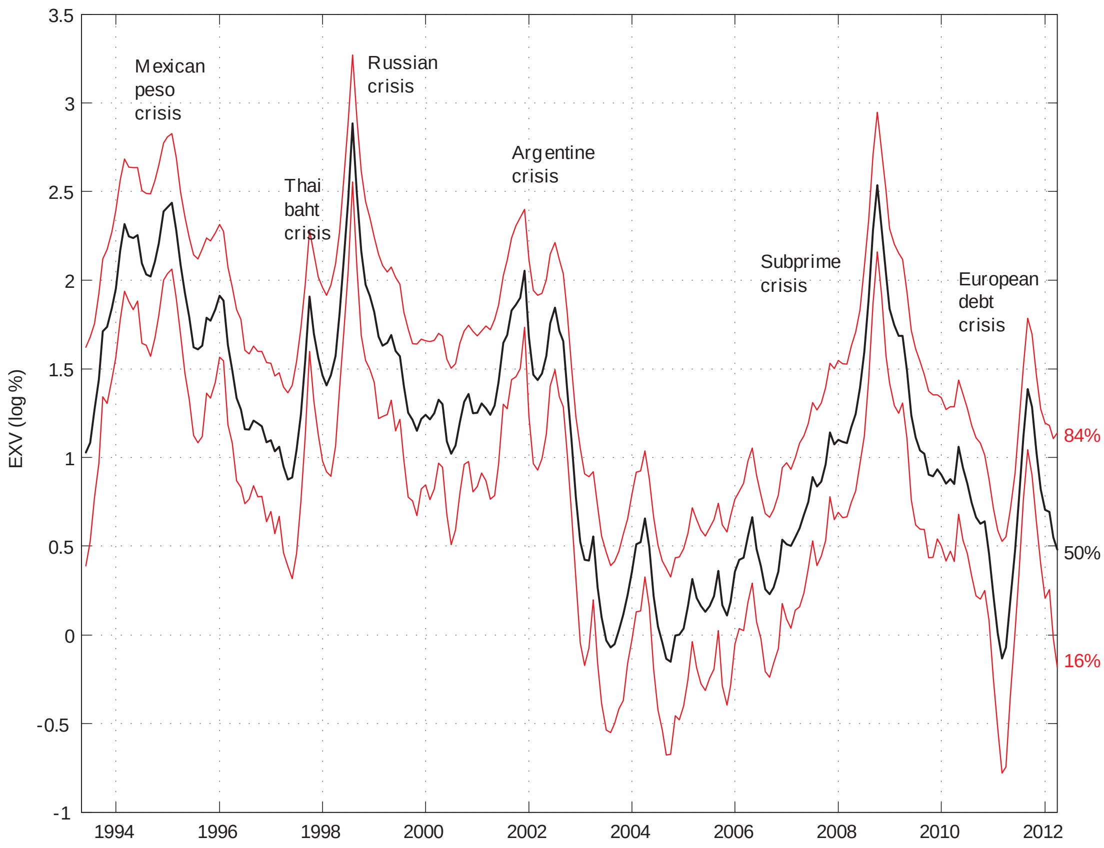

Figure 1: External volatility indicator (EXV).

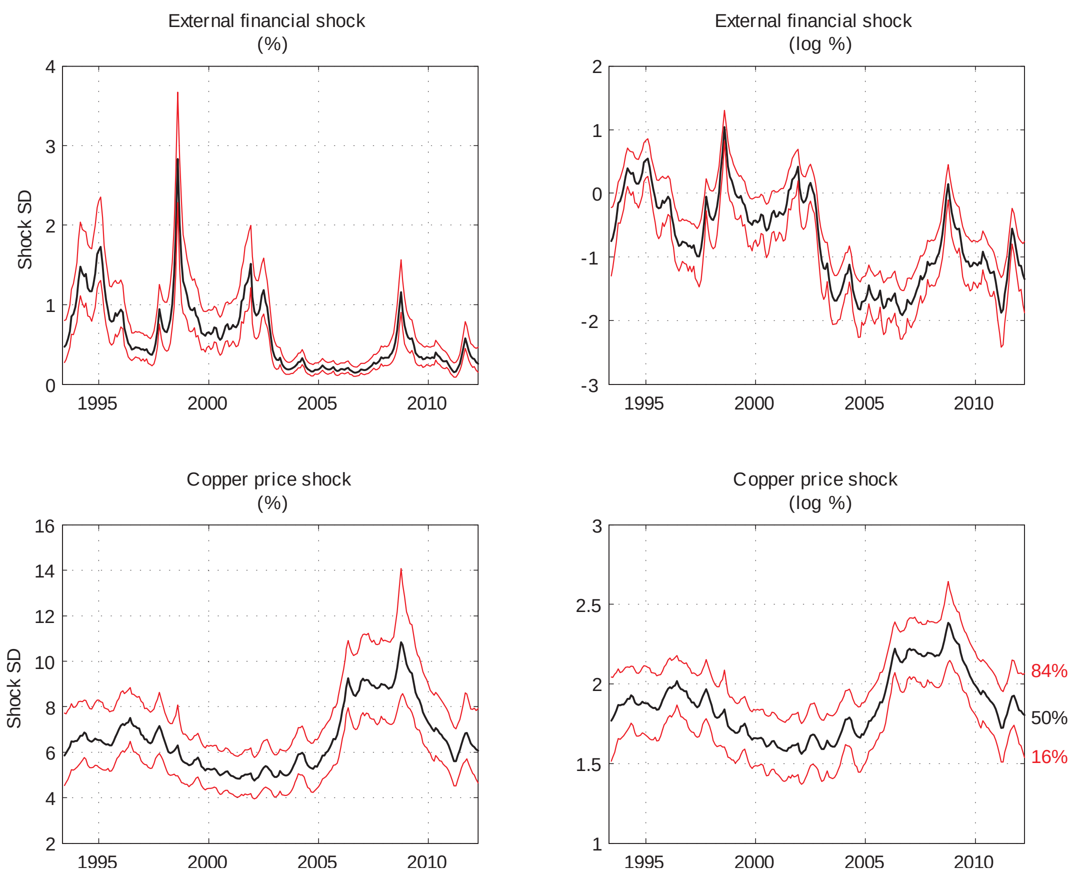

Figure 2: Standard deviations of external shocks.

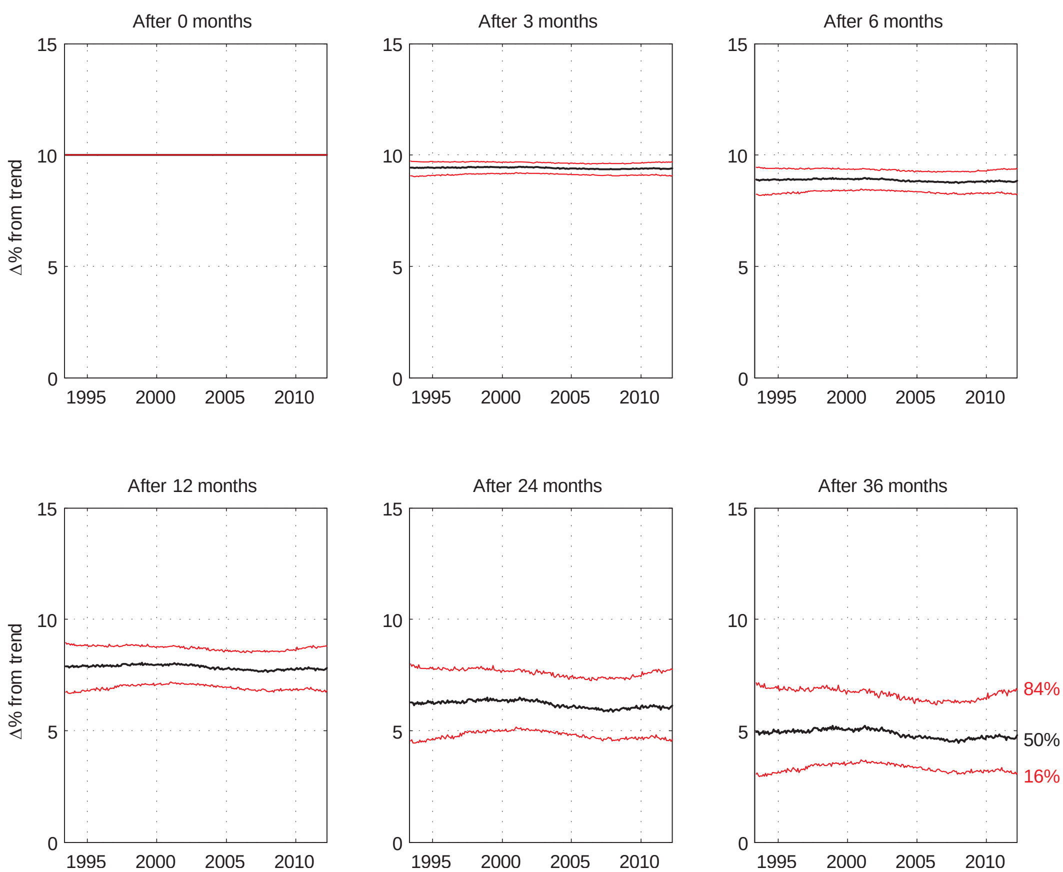

Figure 3: Responses of copper price to copper price shocks (10%).

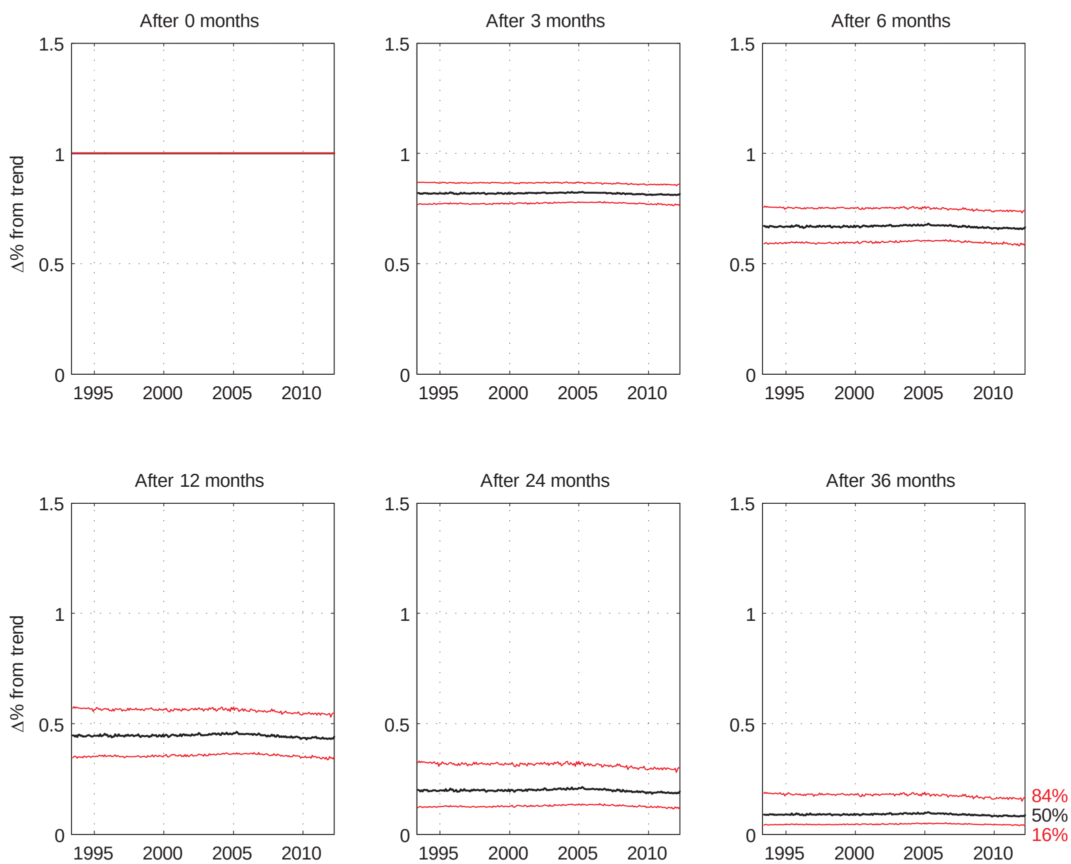

Figure 4: Responses of emerging market spreads to financial shocks (100 b.p.).

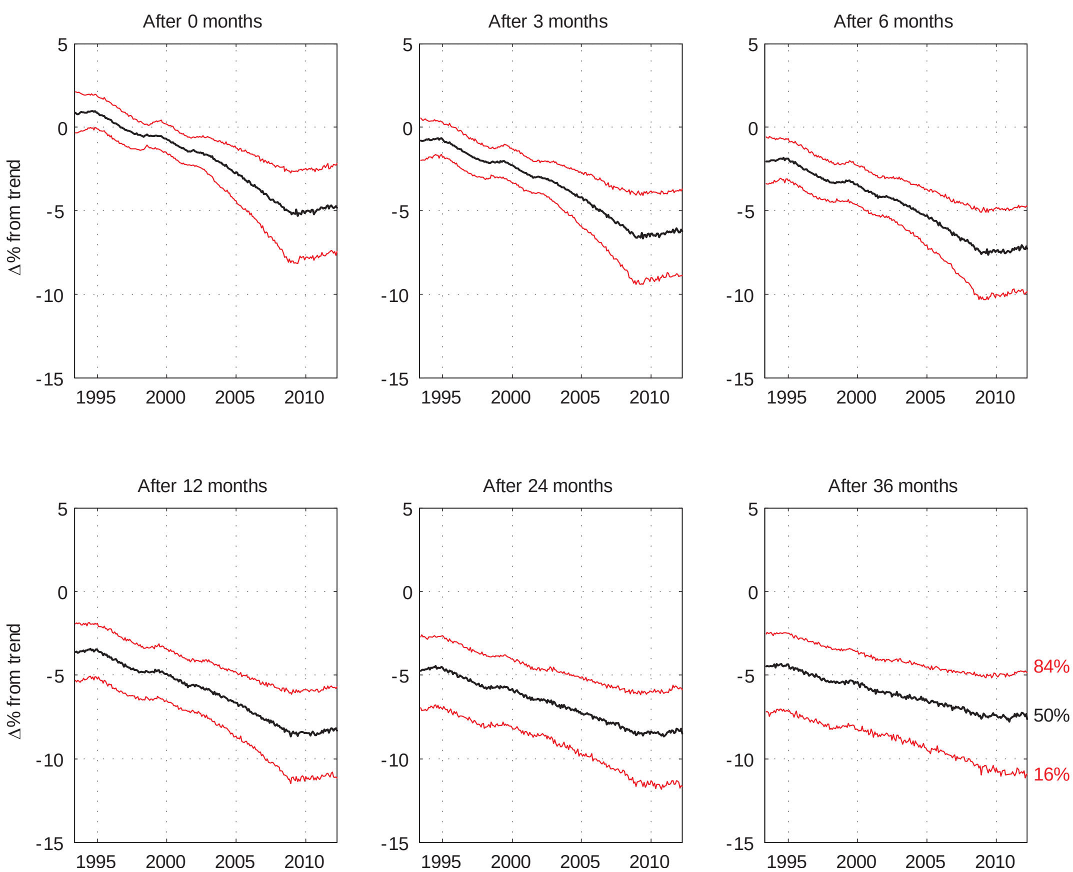

Figure 5: Responses of copper price to financial shocks (100 b.p.).

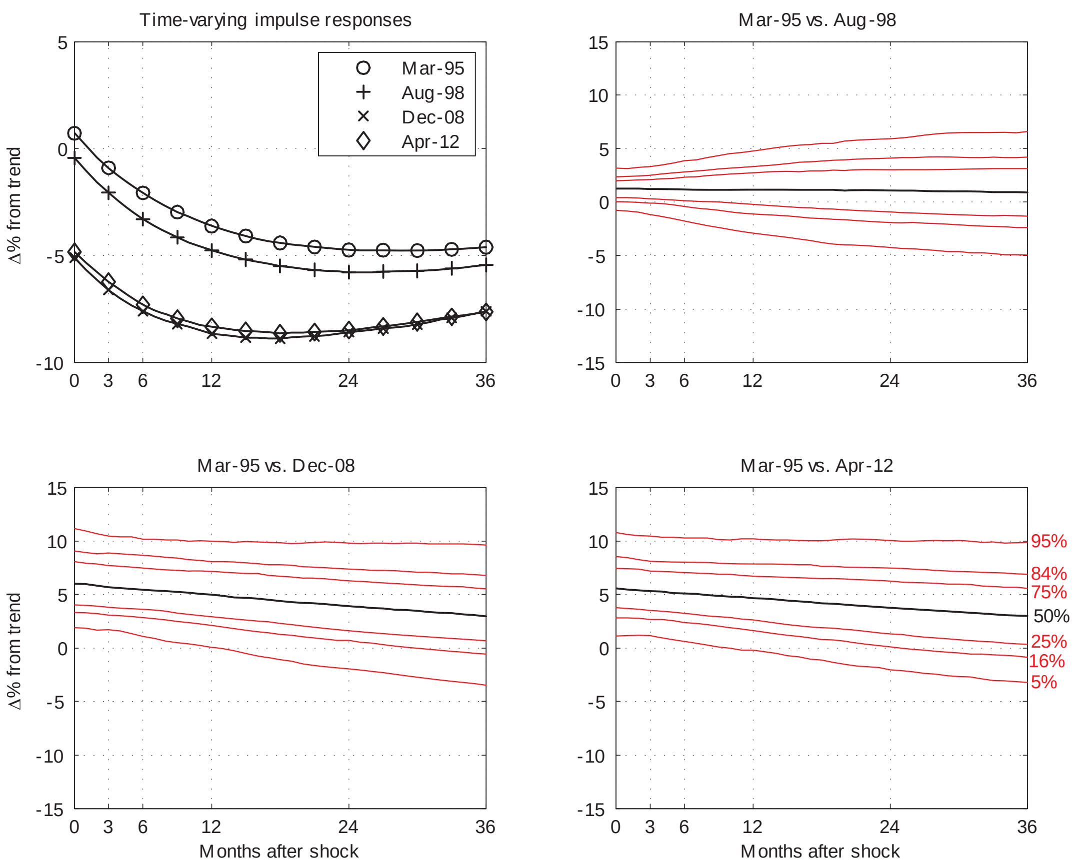

Figure 6: Differences in responses of copper price to financial shocks (100 b.p.).

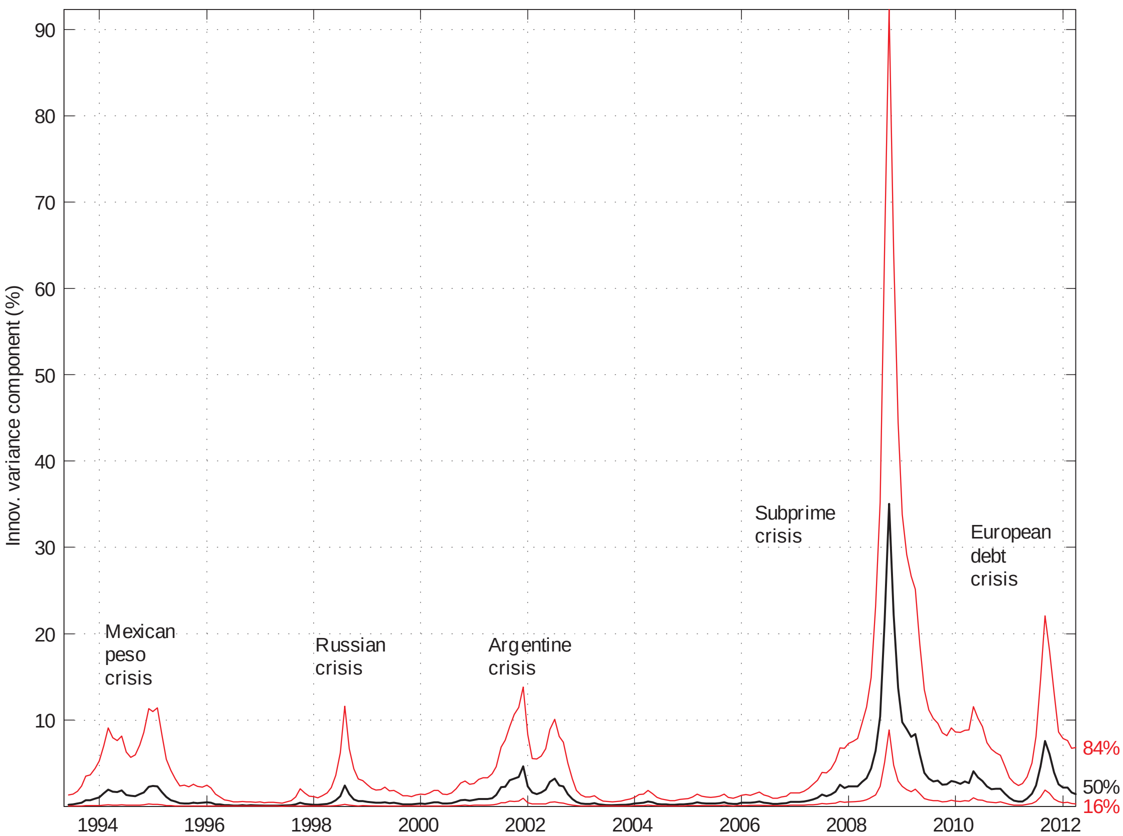

Figure 7: Financial component of copper price innovation variance.

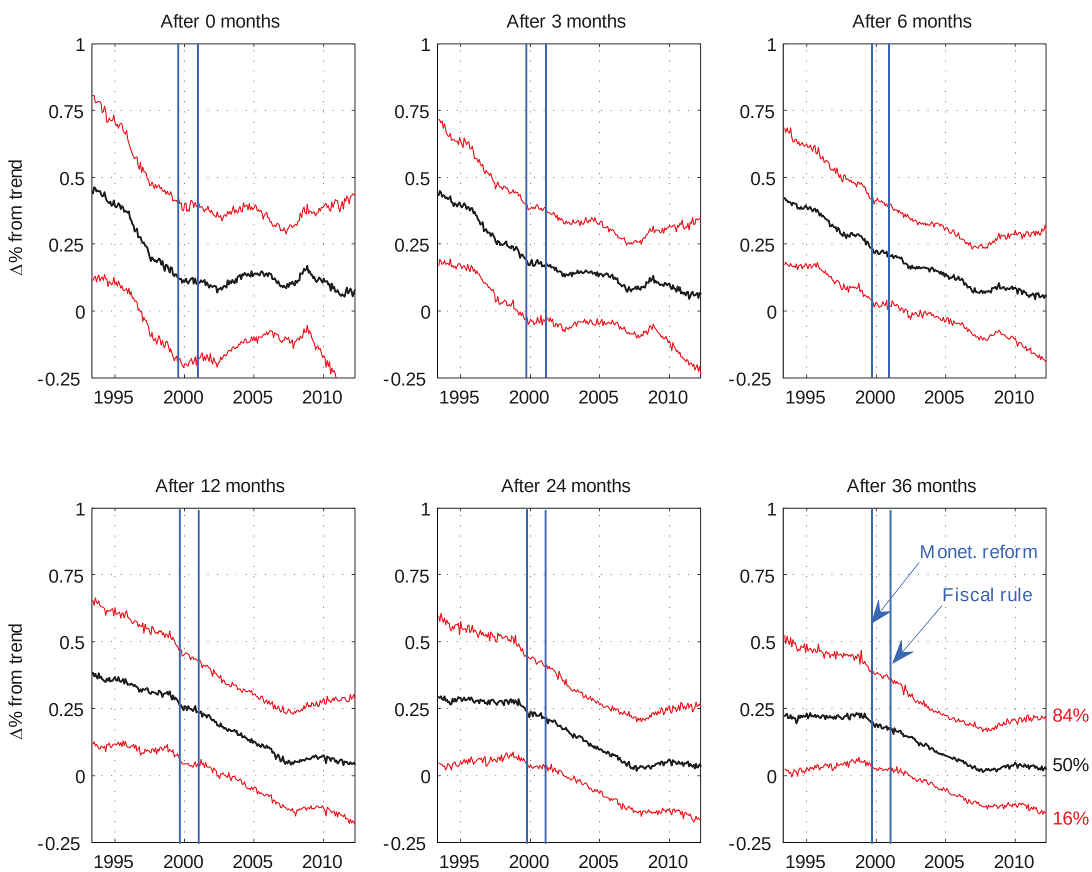

Figure 8: Responses of output growth to copper price shocks (10%).

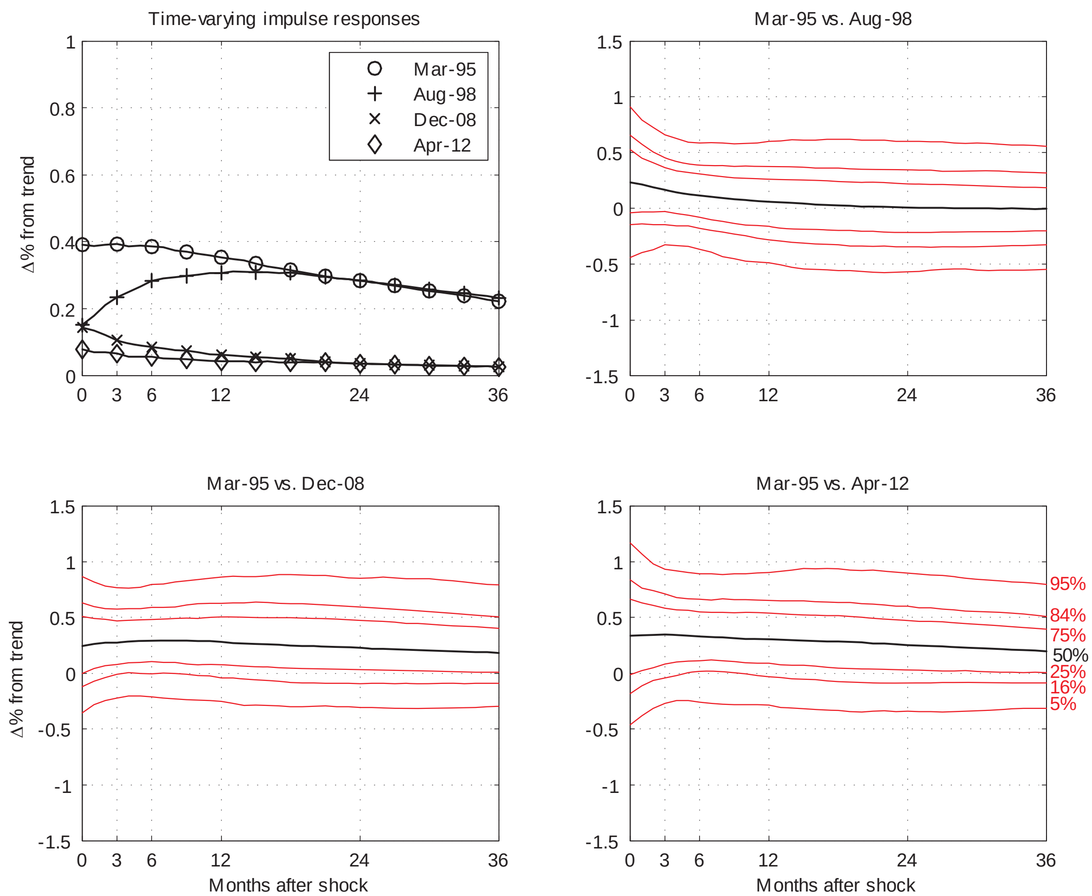

Figure 9: Differences in responses of output growth to copper price shocks (10%).

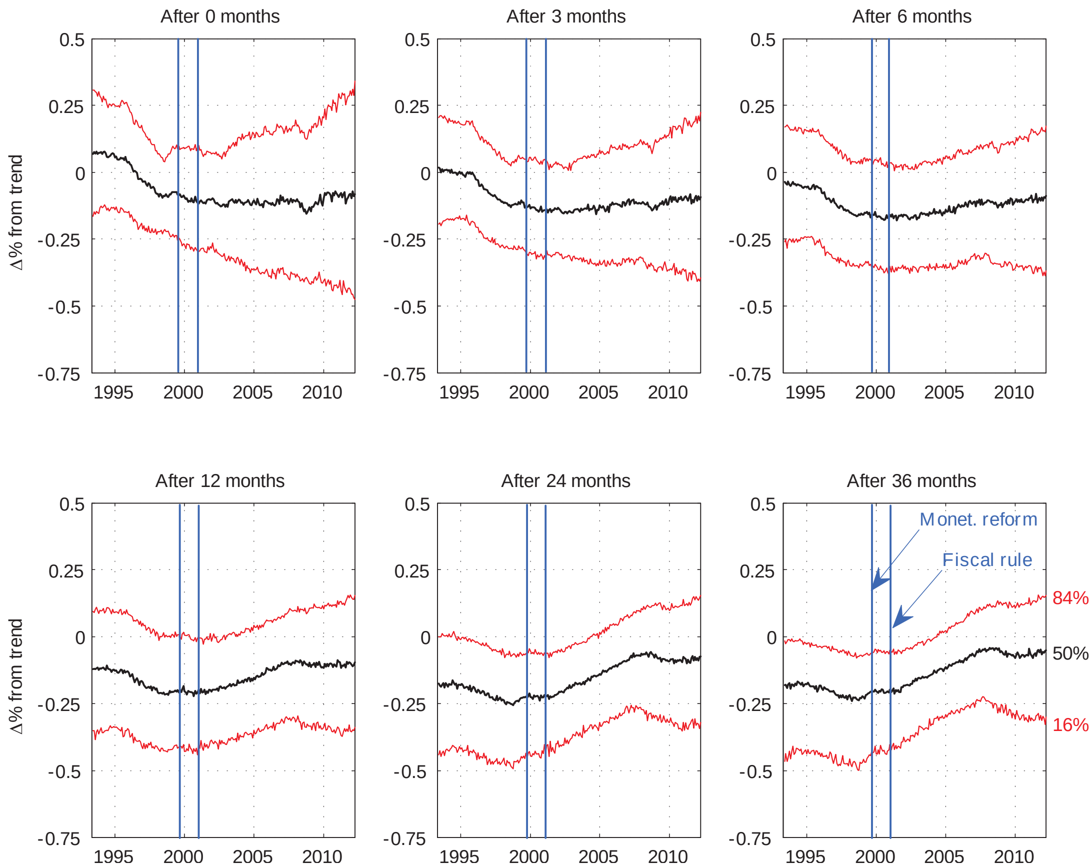

Figure 10: Responses of output growth to financial shocks (100 b.p.).

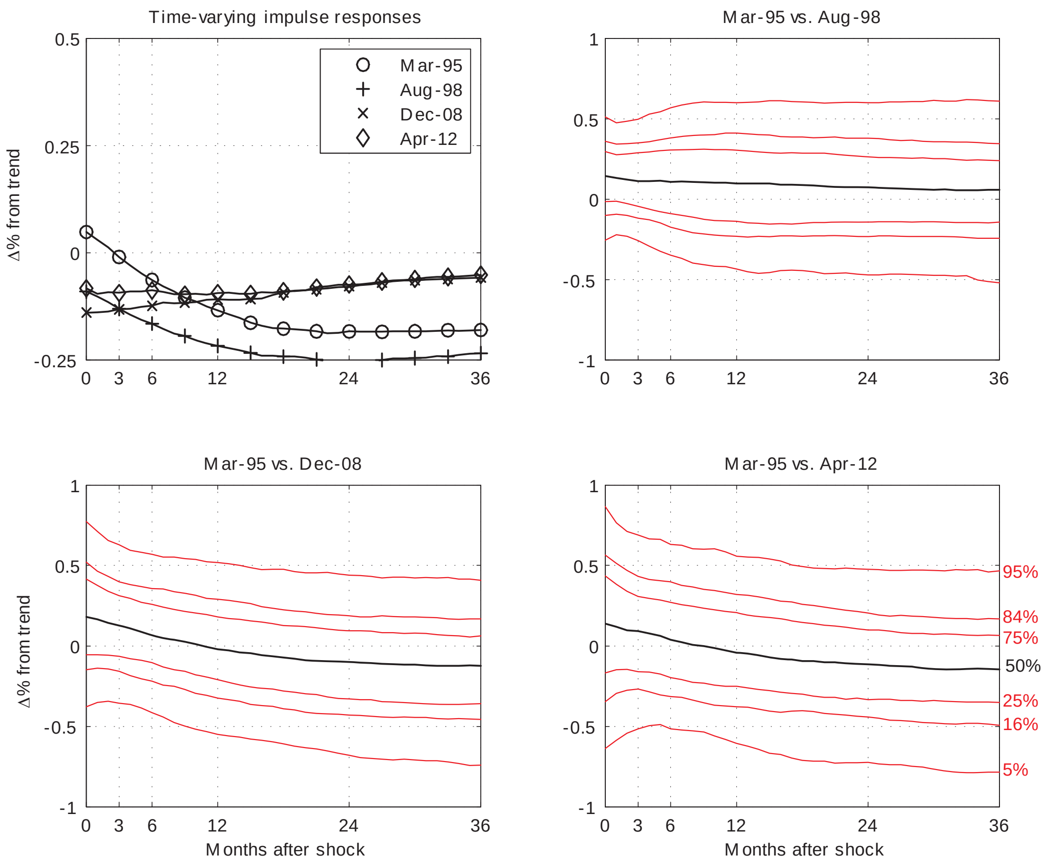

Figure 11: Differences in responses of output growth to financial shocks (100 b.p.).

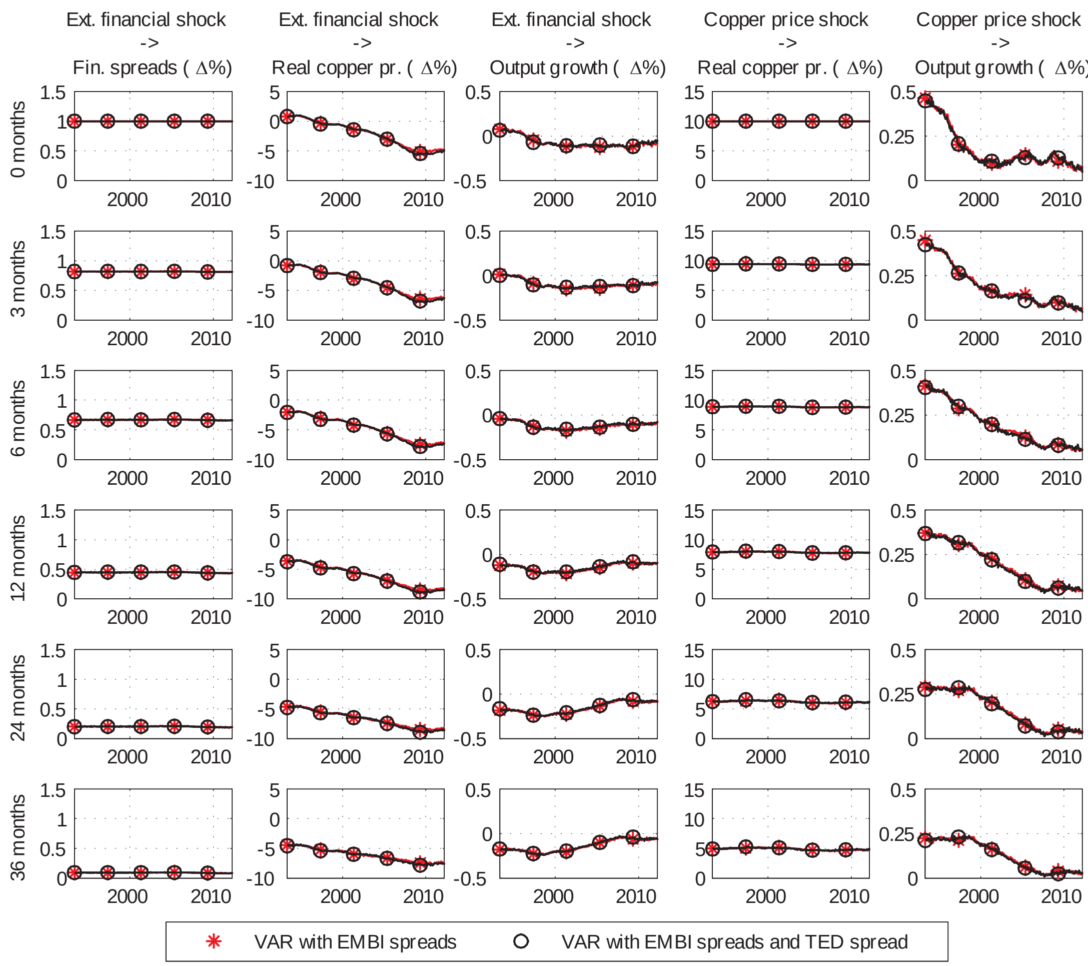

Figure 12: Robustness of estimated impulse responses from VAR with first principal component of EMBI spreads and TED spread versus VAR with EMBI spreads.

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