





How strong is the link between the global financial cycle and national macro-financial dynamics? A wavelet analysis

Christian R. Proaño^{a,b,1,*} , Leonardo Quero Virla^a , Till Strohsal^{c,d}

^a Otto-Friedrich-Universität Bamberg Bamberg, Germany

^b Centre for Macroeconomic Analysis (CAMA), Canberra, Australia

^c Berlin School of Economics and Law, Berlin, Germany

^d Freie Universität Berlin, Berlin, Germany

HIGHLIGHTS

- The evidence in our study reveals that a strong and uniform relationship between the global financial cycle and national macro-financial series exists only during periods of global financial stress.
- Beyond those periods, we find significant variation in the relationship – both across time and countries.
- This variation becomes particularly visible in the frequency domain.

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ABSTRACT

This paper explores the interaction between the global financial cycle (GFCy) and country-specific macro-financial dynamics. We investigate two alternative measures of the GFCy, the CBOE VIX index and Rey (2013)'s global factor, and equity prices, house prices, and aggregate credit volume as national variables. By means of a continuous wavelet analysis and a structural VAR framework, we explore such interaction in the frequency- and time-domain for 12 countries. Our evidence reveals that a strong and uniform relationship between the global financial cycle and national macro-financial series exists only during periods of global financial stress. Beyond those periods, we find significant variation in the relationship – both across time and countries. The choice of the global financial cycle proxy plays a very limited role.

1. Introduction

Over the last decade and mainly as a reaction to the 2008–09 global financial crisis, the *financial cycle* concept has become one of the central topics in the discussion of macroprudential policies and financial regulation. In the policy arena, the European Central Bank (Cabral et al., 2019) highlights the financial cycle as a key variable for systemic risk monitoring in the institution's macroprudential policy framework, while the Bank of International Settlements (2023) and the Deutsche Bundesbank (2022) feature

* Corresponding author at: Otto-Friedrich-Universität Bamberg Bamberg, Germany.

Email address: christian.proano@uni-bamberg.de (C.R. Proaño).

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this concept prominently in recent reports on financial stability. In academic research, the financial cycle has also become standard when discussing systemic risk indicators (Hartwig et al., 2021).

A large segment of the literature on the financial cycle has focused on its measurement and the characterization of its empirical properties (see Claessens et al., 2011; Drehmann et al., 2012 and Borio, 2014, as well as Menden and Proaño, 2017, Strohsal et al., 2018, 2019 and Schüler et al., 2020 for more recent studies). Yet, a parallel line of research has been centered around the notion of a *Global Financial Cycle* (GFCy),² following Rey (2013)'s prominent contribution and the subsequent publications of Passari and Rey (2015) and Miranda-Agrippino and Rey (2015, 2020, 2022). While the national financial cycle can be broadly defined as a self-reinforcing mechanism through which financial risk perceptions and financing constraints lead to a recurrence of booms and busts (Borio, 2014), Rey (2013) introduced the idea of a GFCy in capital flows, asset prices and credit growth, which is negatively correlated with the CBOE VIX and uncorrelated with country-specific macroeconomic conditions.

The existence of the GFCy has been both corroborated by some authors (e.g., Georgiadis and Mehl, 2016; Jordà et al., 2019, Potjagailo and Wolters, 2023) and questioned by others (e.g., Cerutti et al., 2019). Additionally, there is a vast literature on the transmission of international financial shocks (e.g., Eickmeier and Ng, 2015; Abbate et al., 2016 on evidence for developed economies, and Uribe and Yue, 2006; Vicondoa, 2019 on emerging markets). The majority of these studies have relied on time-domain econometric methods, as it is standard in the macroeconomic literature. However, as discussed by Strohsal et al. (2019), the international transmission of risk perceptions and aggregate uncertainty, often proxied by the CBOE VIX, may vary significantly across frequencies. As time-domain techniques cannot identify at which frequencies the financial cycle operates or interacts with other macro-financial variables, various authors have instead opted for frequency-domain methods to explore the time scales behind the cycle. In this regard, Verona (2016); Ardila and Sornette (2016), Altăr et al. (2017); Strohsal et al. (2018, 2019); Schüler et al. (2020), and Mandler and Scharnagl (2022a,b) are key contributions that have typically suggested that financial cycles have time-varying statistical properties and significantly longer durations than business cycles. Particularly, spectral and wavelet methods have been used in this literature.

To the best of our knowledge, the time-varying influence of the GFCy (measured by the CBOE VIX index or by Rey's global factor of asset prices) on national macro-financial dynamics has only been tangentially investigated in the context of the financial cycle literature. This paper addresses this specific gap, in both the time- and frequency-domain, for 12 representative economies, by blending insights from a continuous wavelet analysis³ and a structural vector autoregressive (SVAR) framework. First, our analysis shows that the two leading measures of the GFCy, used interchangeably in the literature, generate roughly similar responses in equity prices and aggregate credit, but not in house prices (except for the US). Second, based on cross-wavelet coherency spectra, our results suggest that the relationship between the GFCy and national macro-financial dynamics varies significantly across time and countries. There is not a uniform, consistent relationship that explains all cases, beyond periods of common, global financial distress. This general finding is robust to the choice of different global financial cycle proxies. The heterogeneity of our results across countries is more visible in the frequency-domain than in the time-domain.

There are at least two theoretical avenues to explain the time-varying, unsystematic nature of the global-national relationship. Primarily, the most evident explanation would be the existence of a global common shock, i.e., the global financial crisis, which affected markets on a global scale differently at specific points in time. A complementary explanation would rather highlight the role of herding behavior and the heterogeneity of agents. In recent work, Coimbra and Rey (2023) proposed a macroeconomic model of the financial cycle where time-varying macroeconomic risk arises from the risk-shifting behavior of heterogeneous financial intermediaries, and additionally, risk concentration and the price of risky assets are driven by high risk-taking intermediaries when they are dominant in the market. Along those lines, the long-standing position of the behavioral finance literature has been that herding behavior in financial markets increases in times of high uncertainty, easing the coordination of heterogeneous economic agents around a common action or strategy (see Shiller and Pound, 1989; Shiller, 1990, and Hommes et al., 2005). For instance, Schmitt and Westerhoff (2017) showed that the trading rules of heterogeneous financial market agents are correlated through herding behavior in times of high market volatility, but their actions are more or less independent in normal times. Taking all these views into consideration, the link between the GFCy and national macro-financial variables should not be taken as constant over time.

The remainder of the paper is organized as follows. In Section 2, we describe the continuous wavelet analysis methodology and the SVAR estimation; details about the sample and country selection are available in the Appendix. In Section 3, we address the interaction between the two leading measures of the GFCy in a wavelet analysis, followed by a deeper inspection of the interaction between the GFCy and national macro-financial dynamics in both the frequency- and time-domain, in Section 4. Finally, we draw some conclusions from the study in the last section.

2. Econometric methodology

We use two econometric methodologies to investigate the interaction between the GFCy and national macro-financial dynamics: a wavelet analysis for the frequency-domain and a conventional SVAR approach for the time-domain. While the latter corresponds to the standard macroeconometrics toolkit (see Kilian and Lütkepohl, 2017), the popularity of the former is growing in empirical research, as it provides a reliable alternative for studying changes and structural breaks in the periodic behavior of time series, and in the interactions between time series. More specifically, it is particularly useful for analyzing economic variables that display different

² Henceforth, we will use the "GFCy" abbreviation to denote the global financial cycle, as in Cerutti et al. (2019), given that "GFC" is commonly associated with the global financial crisis.

³ Mandler and Scharnagl (2022a,b) touched upon a tangential topic.

behavior at distinct periods of time (Crowley, 2007; Aguiar-Conraria and Soares, 2014; Rua, 2012). Gallegati and Semmler (2014) provide an extensive edited volume with wavelet analysis applications in economics.

A full description of the sample (variables, countries and years) used in the wavelet and SVAR analyses is available in Appendix A.

2.1. Continuous wavelet transform

The starting point of the wavelet methodology lies in the notion of small waves that can be stretched and compressed. A so-called mother wavelet $\psi(t)$ can be understood as a template which creates other wavelets by compressing, stretching and shifting along the time axis. As the term implies, wavelets are small waves which can exhibit various shapes, but generally share one property: at least once they oscillate around the time axis. The choice of the mother wavelet depends on the application at hand and on the type of the variable to be analyzed (Ramsey, 2014; Aguiar-Conraria and Soares, 2014). The *Haar*, *Mexican hat* and *Morlet* wavelets are established mother wavelets in the broader literature. We use the Morlet wavelet as it is the preferred choice in the economics literature (see Verona, 2016; Aguiar-Conraria and Soares, 2011, 2014; Mandler and Scharnagl, 2022b). Namely:

$$\psi_{\omega}(t) = \pi^{-1/4} e^{i\omega t} e^{-t^2/2}, \quad (1)$$

where the angular frequency or rotation rate in radians per time unit ω is set to six.⁴

The continuous wavelet transform for the time series $x(t) \in L^2(\mathbb{R})$ with respect to a given mother wavelet ψ is then given by

$$W_{x;\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s} \right) dt, \quad (2)$$

where $\psi^*(\cdot)$ denotes the complex conjugate, with τ determining the position of the wavelet in the time domain and s its position in the frequency domain.

As the Morlet wavelet is complex-valued, the corresponding wavelet transform of $x(t)$ is also complex-valued and can be decomposed either into its real part $\Re\{W_x(\tau, s)\}$ and imaginary part $\Im\{W_x(\tau, s)\}$, or into its *amplitude* $|W_x(\tau, s)|$ and *phase-angle* (or simply *phase*) $\phi_x(\tau, s) : W_x(\tau, s) = |W_x(\tau, s)|e^{i\phi_x(\tau, s)}$.

Using the continuous wavelet transform, the wavelet power spectrum (WPS) is defined as

$$WPS_x(\tau, s) = |W_x(\tau, s)|^2. \quad (3)$$

where the WPS is simply the square of the amplitude $|W_x(\tau, s)|$ and measures across time and scales the contribution to the variance of the series. It can be interpreted as the local variance of the time series $x(t)$.

Further, the cross-wavelet transform $W_{xy}(\tau, s)$ of the two time series $x(t)$ and $y(t)$ is defined as:

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s), \quad (4)$$

where W_x and W_y represent the wavelet transforms of $x(t)$ and $y(t)$, respectively, and the star denotes the complex conjugate. Further, $|W_{xy}|$ is the cross-wavelet power spectrum of the two time series. It reveals the local covariance between the two time series at each time and scale and indicates the similarity of power between the time series (Aguiar-Conraria and Soares, 2011).

The wavelet coherency (i.e., the absolute value of the complex wavelet coherency) can be interpreted as the local correlation in time and frequency between $x(t)$ and $y(t)$, and can be computed using the continuous wavelet transform as in Eq. (2) of $x(t)$ and $y(t)$ and their cross-wavelet transform as in Eq. (4):

$$R_{x,y}(\tau, s) = \frac{|S(W_{xy}(\tau, s))|}{[S(|W_x(\tau, s)|^2)S(|W_y(\tau, s)|^2)]^{1/2}}, \quad (5)$$

with $0 \leq R_{x,y}(\tau, s) \leq 1$, and where S is a smoothing operator.⁵ In the choice of the smoothing operator, we choose to smooth in time and scale directions by using the Hamming window with a constant window size of three for both time and scale.

By means of the wavelet coherency, it can be detected at which frequencies two time series comove across time, but this yields no information about the algebraic sign of the correlation. Information about this and the lead-lag relationships between $x(t)$ and $y(t)$ is provided by the *phase difference*:

$$\phi_{x,y}(\tau, s) = \arctan \left(\frac{\Im\{W_{xy}(\tau, s)\}}{\Re\{W_{xy}(\tau, s)\}} \right), \quad (6)$$

where the imaginary and real parts of the complex cross-wavelet transform are again denoted by \Im and \Re . The phase difference $\phi_{x,y}(\tau, s)$ is denoted in radians and can feature values $\phi_{x,y}(\tau, s) \in [-\pi, \pi]$, whereas the values can be classified and interpreted in the following way:

⁴ A higher value of ω improves the frequency localisation but also leads to a poorer time localisation (Rua, 2012, p. 4). According to Aguiar-Conraria and Soares (2014), the choice of six implies an optimal time-frequency resolution and yields a simple relation between scale (s) and frequency (ω), $\omega \approx \frac{1}{s}$.

⁵ Smoothing is necessary both in time and in scale, as without smoothing coherency would be identical to one at all scales and times (Aguiar-Conraria and Soares, 2011). Aguiar-Conraria and Soares (2014) refer to Cazelles et al. (2007) on this topic. In the literature, there is no general agreement about the direction (time, scale or both) and magnitude of smoothing to get an appropriate measure of coherency. According to Grinsted et al. (2004), the smoothing operator should be designed in a way that it has a similar footprint as the used mother wavelet.

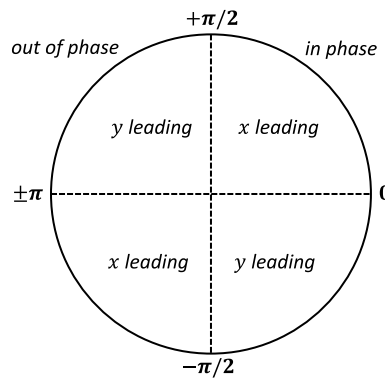


Fig. 1. Phase difference interpretation.

$$\phi_{x,y}(\tau, s) \in \begin{cases} (0, +\frac{\pi}{2}) & \text{in phase, } x(t) \text{ leading} \\ (+\frac{\pi}{2}, +\pi) & \text{out of phase, } y(t) \text{ leading} \\ (-\pi, -\frac{\pi}{2}) & \text{out of phase, } x(t) \text{ leading} \\ (-\frac{\pi}{2}, 0) & \text{in phase, } y(t) \text{ leading} \end{cases} \quad (7)$$

or simply as depicted in Fig. 1.

The cross-wavelet coherency graphs shown throughout the paper can be interpreted as follows. The color indicates the strength of the coherency, i.e., the warmer the color, the stronger the coherency. The presence of arrows indicates the existence of a significant lead-lag relationship (area of significance), and the direction of the arrows indicates which variable leads in the relationship and whether the series are in phase or anti-phase (as indicated in Fig. 1). For example, arrows pointing to the left indicate that the series are anti-phase and move in the opposite direction, while arrows pointing up and to the right, or down and to the left, indicate that the first variable (the GFCy proxy in our case) is leading. Moreover, the cone of influence where results can be interpreted is depicted by the light-shaded areas towards the upper ends of each plot. Results falling outside such cone (i.e., those falling in the light-shaded area) should be interpreted with caution.

Through the wavelet analyses, we then study the time-varying relationship between the GFCy (proxied by the CBOE VIX and Rey's global factor of asset prices) and each of the country-specific proxy variables of the domestic financial cycle (i.e., equity prices, house prices, and aggregate credit for country, following Drehmann et al., 2012). There, we will consistently associate $x(t)$ with one of the two measures of the GFCy, and $y(t)$ with the country-specific variable.⁶ It should be noted that the continuous wavelet transform offers a convenient framework to explore time-varying relationships, but it does not allow for much structural interpretation.

2.2. Structural vector autoregressive analysis

As a complement to the wavelet analysis, we conduct a recursively-identified structural vector autoregressive (SVAR) analysis,⁷ an established approach in empirical macroeconomics.⁸ We provide further details about the methodology in Appendix B. Similar to Strohsal et al. (2019), the SVAR models are estimated on a country-specific basis and include: a proxy of the GFCy (the CBOE VIX or Rey's global factor of asset prices), real GDP, real aggregate credit, real equity prices, and real house prices. Specifically, the global financial cycle series is ordered first. Following proposition 3.1 in Pesaran and Shin (1998), the *orthogonalized* impulse responses to a shock in the first equation of a recursively-identified VAR model (the global financial cycle equation, in our case), are equivalent to the *generalized* impulse responses (GIRFs) to that shock, which are in turn considered to be invariant to the ordering of the variables. The GIRFs allow us to analyze how macro-financial dynamics react to a GFCy shock. Nonetheless, the structural interpretation of these results is limited as we cannot draw conclusions about the causes behind the GFCy shock itself.

Considering the negative correlation between the CBOE VIX and Rey's global factor of asset prices, already noted by Rey (2013), and visible in Fig. 2 from 2000 until the end of the sample, we compute responses to a negative shock (i.e., a decrease) in the CBOE VIX and to a positive shock (i.e., an increase) in Rey's factor.

The lag order is set to $p = 4$ in all cases, in line with common practices regarding quarterly data (e.g., see Chapter 2 of Kilian and Lütkepohl, 2017). Lag-length criteria were also inspected accordingly.

⁶ Panel (c) of Fig. 2 is the only exception where $x(t)$ is the VIX and $y(t)$ is Rey's factor.

⁷ An obvious alternative approach would be to estimate panel VARs for country groups. This would, however, blur the comparison of the results between the time- and frequency-domain, and neglect the country-specific nature of national financial cycles.

⁸ See Kilian and Lütkepohl (2017) for a comprehensive textbook treatment of SVAR models.

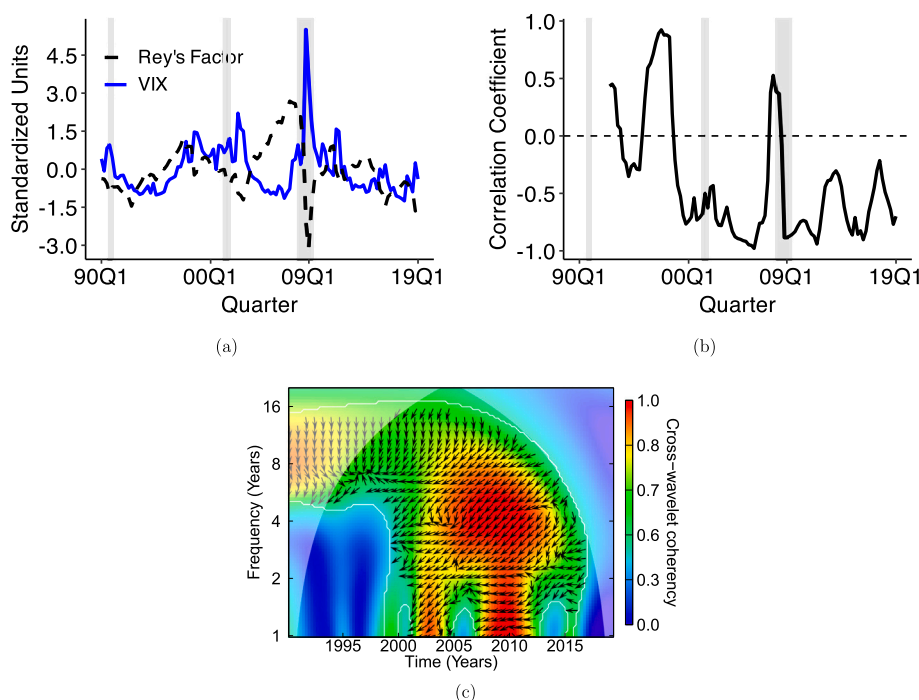


Fig. 2. Standardized VIX and Rey's Global Factor of Asset Prices 1990Q1-2019Q1: (a) Line plot; (b) Rolling correlation: on a 12-month window; (c) Wavelet Coherency. Note: Gray-shaded areas denote NBER recession periods for the US economy; to enable a reasonable graphical comparison, both variables were standardized for this part of the analysis. In the remaining computations, the series are transformed as indicated in the [Appendix A](#). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3. The CBOE VIX and Rey's global factor of asset prices

The CBOE VIX and Rey's global factor of asset prices are the two leading measures of the GFCy in the literature. Nevertheless, only a few authors (e.g., see [Cerutti et al., 2019](#); [Tian et al., 2023](#)) have conducted their analyses using various proxies of the GFCy. Usually, only one measure is considered, most probably due to the belief of a correlation between the VIX and the global factor, which [Rey \(2013\)](#) put forward in her influential contribution.

[Fig. 2](#) shows the two series between 1990Q1-2019Q1. In the time domain (Panel A), it is evident that the series moved in opposite directions most of the time. Additionally, the sign of the rolling correlation (Panel B) is mostly negative but not constant over time. It should be noted that the timespan starting in the early 2000s until the immediate period preceding the global financial crisis was characterized by a decrease in the VIX along with a gradual increase in Rey's global factor. This is consistent with the notion of a *volatility paradox* ([Brunnermeier and Sannikov, 2014](#)) where a low volatility environment may motivate market participants to take more risk, which in turn might increase the fragility of the financial system, i.e., instabilities can arise even when the aggregate risk level is low.⁹

In the frequency domain (Panel C), we observe medium coherency between the two series at frequencies between 5 and 16 years during the 1990s, although no systematic lead-lag relationship can be detected for this period. In the first-half of the 2000s, the strength of the coherency stays at similar levels, but the area of significance becomes larger and covers all frequencies. Around the onset and occurrence of the global financial crisis, the coherency between the two GFCy proxies peaks at high and medium frequencies, with the CBOE VIX now leading primarily at frequencies between 3 and 8 years, as arrows point down and to the left. The fact that arrows never point to the right indicates that the two series do not move in the same direction. Finally, there seems to be no statistically significant coherency between 2015 and the end of the sample in 2019.

The presumption of a close relationship between the two leading GFCy measures, motivated by the work of [Rey \(2013\)](#) and [Miranda-Agrippino and Rey \(2015\)](#), and which has also gained traction in the literature, should be assessed carefully depending on the case at hand (see also [Cerutti et al., 2019](#)). The two measures clearly do not interact uniformly across time and frequencies, probably due to the different underlying economic forces behind them: While the CBOE VIX reflects 30-day-ahead implied volatility expectations on the S&P 500 and is derived from option prices (essentially, a forward-looking measure), the global factor of asset prices estimated by [Rey \(2013\)](#) and [Miranda-Agrippino and Rey \(2022\)](#) is based on realized, historical asset price returns (a backward-looking measure). Standard economic intuition suggests that the VIX should be ahead of developments in financial markets. That said, providing a new concept for the GFCy is outside the scope of this paper. We will analyze the interaction between the two widely accepted GFCy proxies and the national macro-financial series in the following sections.

⁹ This idea is not too distant from the Minskyan view on financial markets.

4. Interactions between global financial cycle proxies and national macro-financial dynamics

Our characterization of the interaction between the GFCy and the national macro-financial dynamics is conducted in two steps. First, we use country-specific SVAR models to explore the effects of a GFCy shock on national macro-financial series. Since we use two different GFCy proxies which mostly move in opposite directions (see Section 3), we propose investigating a GFCy shock through a negative shock to the CBOE VIX and a positive shock to Rey's global factor, respectively. After the SVAR analysis, we inspect the relationship through bivariate wavelet analyses. Both methodologies follow the specifications listed in Section 2.

4.1. Equity prices: coherency and impulse responses

In the time-domain, the impulse responses from the SVAR analysis show a relatively uniform pattern. A GFCy shock—a decrease in the CBOE VIX (Fig. 3) and an increase in Rey's global factor (Fig. 4)—produces a significant increase in equity prices lasting around 4 quarters across most countries.

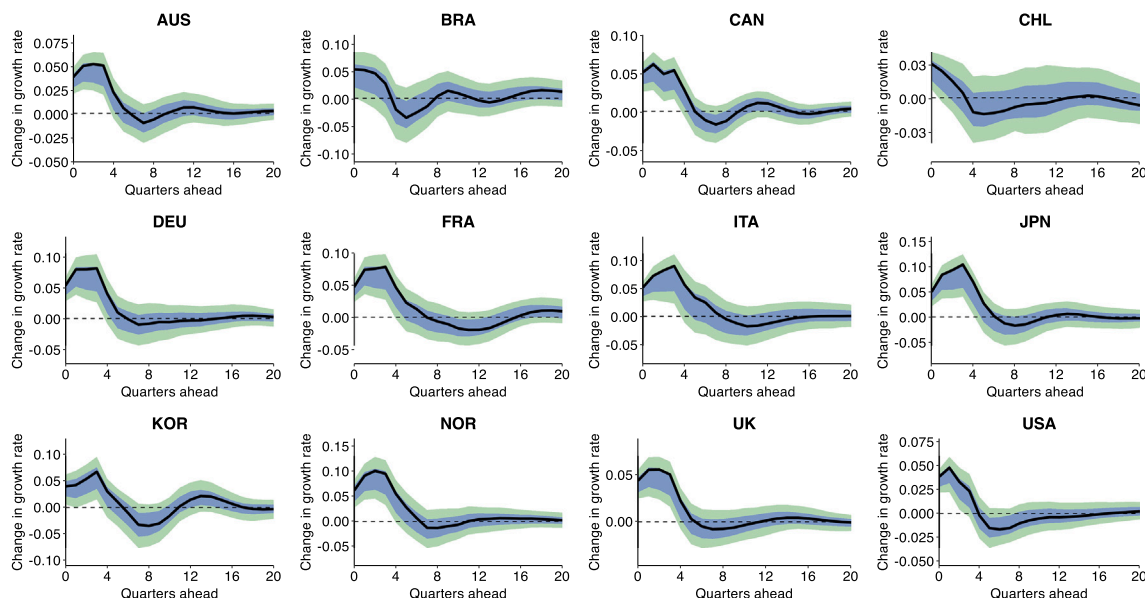


Fig. 3. Responses of Real Equity Prices to a negative one-standard deviation shock in the CBOE VIX. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

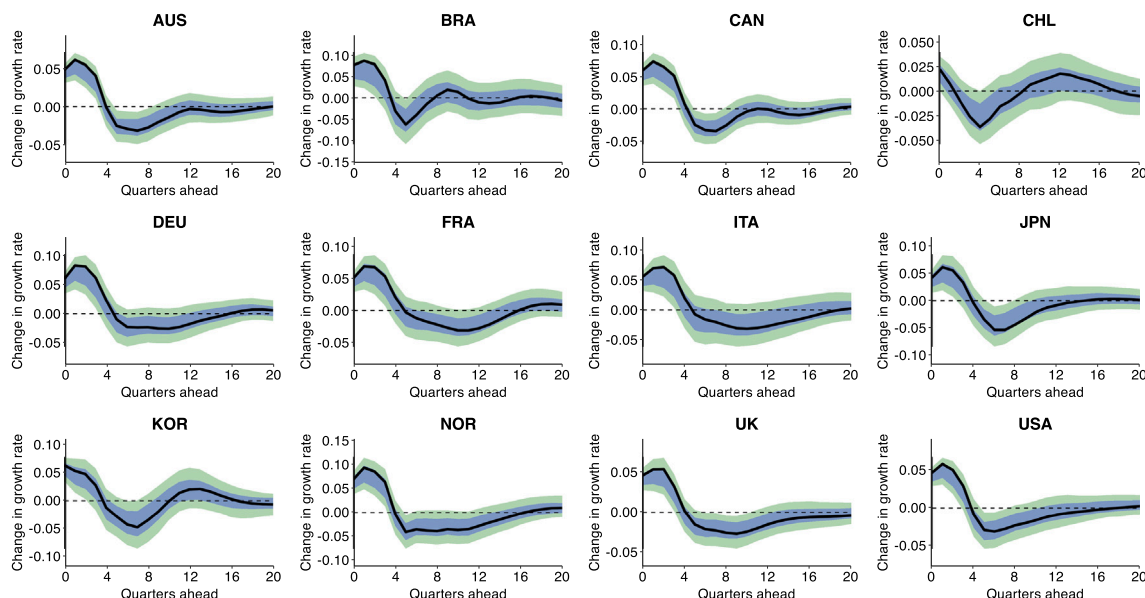


Fig. 4. Responses of Real Equity Prices to a positive one-standard deviation shock in Rey's Global Factor. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

In the frequency-domain, the cross-wavelet coherency graphs show that when the GFCy is measured by the CBOE VIX (Fig. 5), equity prices display the strongest coherency around the years of the global financial crisis. However, the frequency and time range differ across countries. For almost all countries, the coherency is most pronounced at frequencies between 2 and 8 years. Notable exceptions are Australia and Norway, where coherency is strongest at cycles of 8 years and longer. Further, although no systematic lead-lag relationship between the VIX and country-specific equity prices can be observed, the series are mostly in anti-phase (i.e., arrows pointing to the left) in the areas of strongest coherency and therefore move in opposite directions.

In addition, the cross-wavelet coherency graphs between Rey's global factor and equity prices provide a similar picture (Fig. 6). Nonetheless, the areas of significant coherency are larger for all countries and the coherency is stronger at longer cycles compared to the results with the VIX. The US, Canada, the UK, Germany, Australia, and Norway exhibit a strong coherency running through the early 2000s until 2015. The coherency in Japan, Korea, and the remaining European countries is visible around the years of the global financial crisis and the multi-year European debt crisis, but not before that. Moreover, Brazil and Chile are only influenced by the GFCy at higher business cycle frequencies. The lead-lag relationship in these cases is slightly clearer with arrows pointing to the

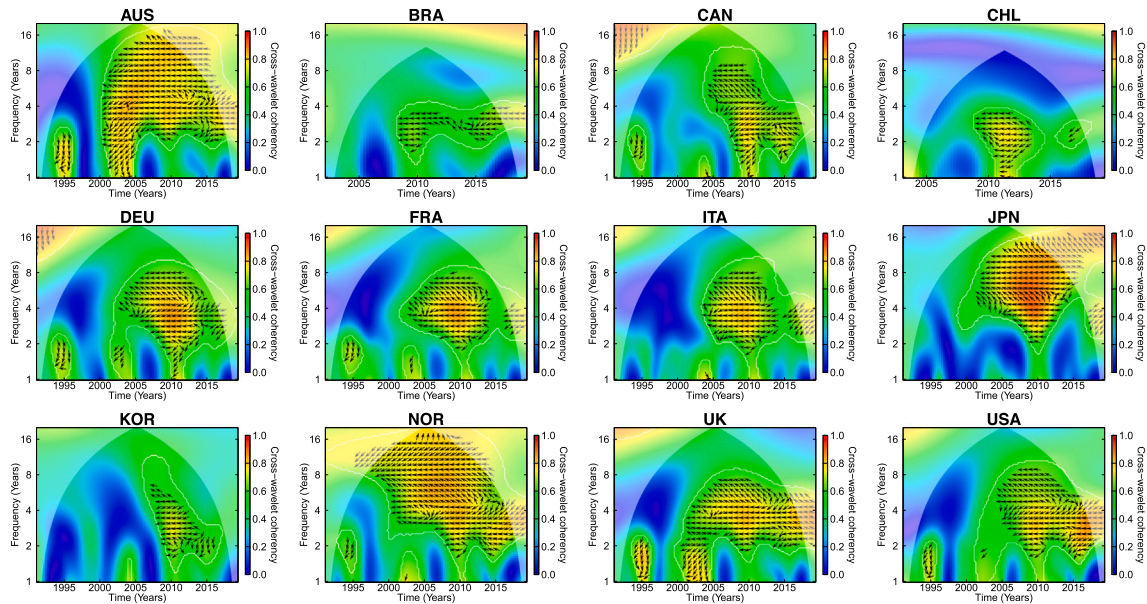


Fig. 5. Cross-Wavelet Coherency Spectra between the CBOE VIX and Real Equity Prices.

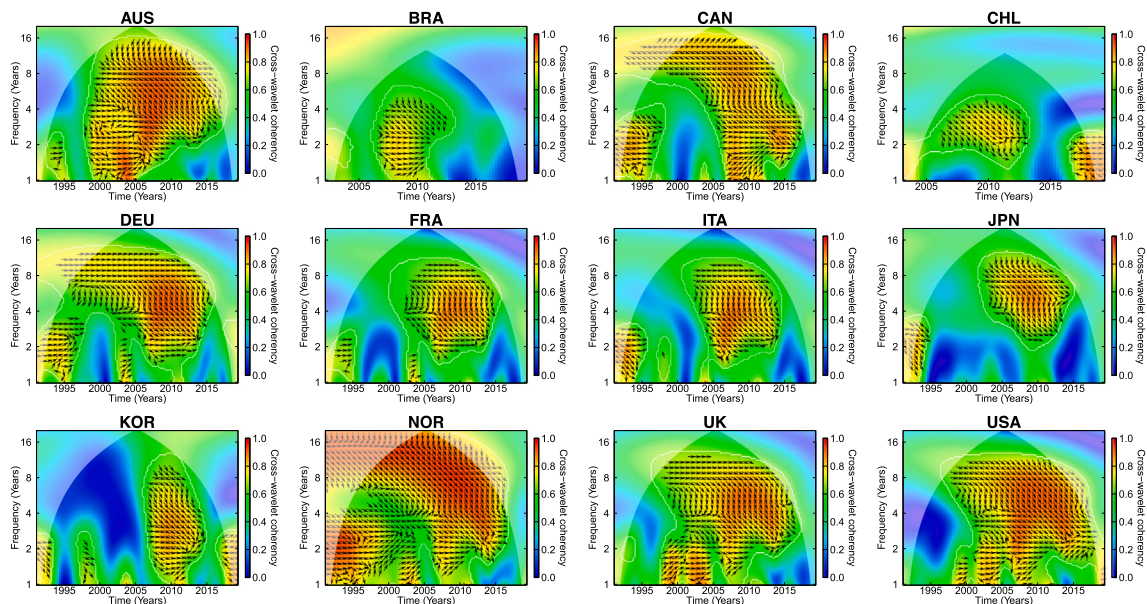


Fig. 6. Cross-Wavelet Coherency Spectra between Rey's Global Factor and Real Equity Prices.

right, or down and to the right, indicating that the relationship is either in phase and occasionally led by Rey's global factor. Such a procyclical relationship is, naturally, not surprising considering that Rey's global factor can be interpreted as a common component of realized equity price returns.

4.2. House prices: coherency and impulse responses

Regarding the relationship between the GFCy and house prices, we obtain heterogeneous results from the SVAR analysis across countries (see Figs. 7 and 8). A GFCy shock generates a decline in house prices, on impact or after some lags, in the US, UK and France, for example. For many other countries, the effect of a GFCy shock appears insignificant, even when judging from the one-standard deviation (68 %) confidence level. Interestingly, for most countries the impulse responses feature a similar shape when comparing the use of the CBOE VIX to the use of Rey's global factor as GFCy proxy.

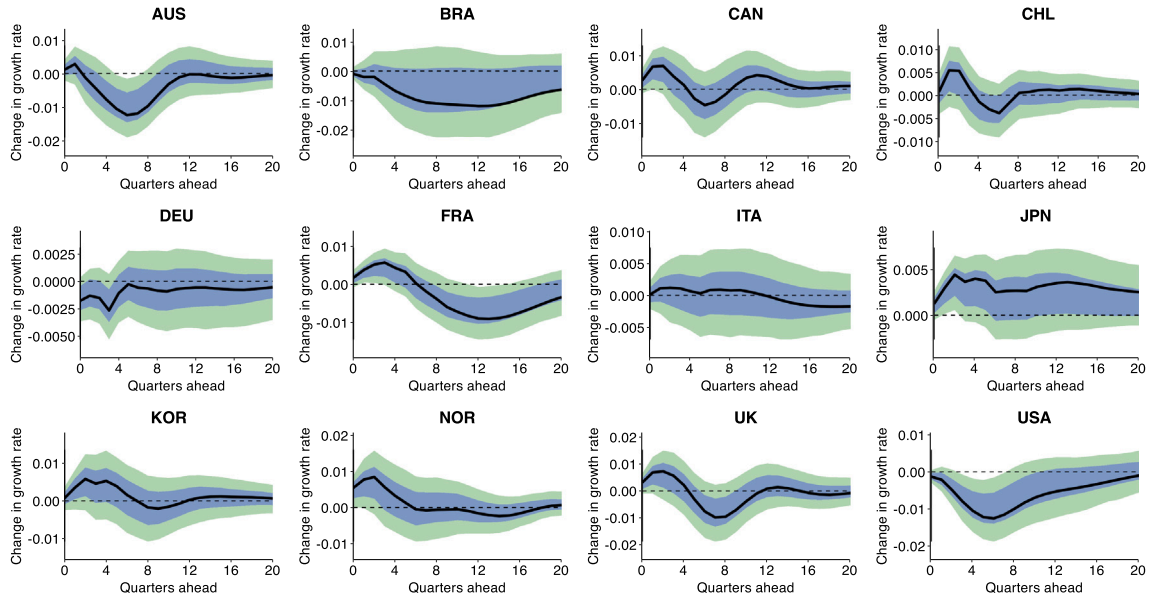


Fig. 7. Responses of Real House Prices to a negative one-standard deviation shock in the CBOE VIX. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

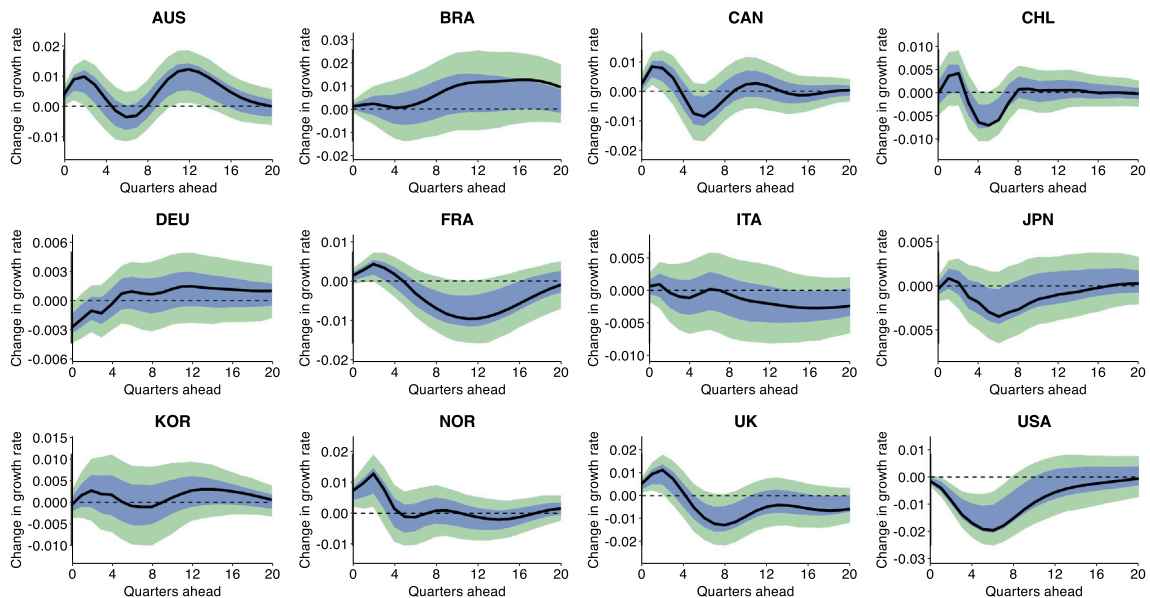


Fig. 8. Responses of Real House Prices to a positive one-standard deviation shock in Rey's Global Factor. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

Turning to the frequency-domain, we note that the cross-wavelet coherency between the CBOE VIX and house prices is generally weak in all countries, except for the US, France and Norway (Fig. 9). For the US, arrows point up and to the left, indicating that house prices lead in the relationship. The area of strongest coherency takes place between 2005 and 2015 at frequencies between 3 and 10 years. Alternatively, arrows point mostly to the left for France and Norway, indicating that the series are in anti-phase. It is important to remark that the remaining countries only display some coherency at specific periods of time, and no lead-lag relationship is visible at all for Germany. In general, our frequency-domain results are in line with the finding of many insignificant impulse responses in the time-domain.

When we consider Rey's global factor as the GFCy proxy (Fig. 10), the cross-wavelet coherencies appear qualitatively similar. The US, France and Norway display the largest areas of coherency, without a common lead-lag relationship being identified. Coherency is most visible around the years of the global financial crisis and at frequencies between 2 and 12 years for those three countries. For the UK, Canada, and Australia, we only see smaller areas of coherency at the end of the 2000s, while the remaining countries have their own coherency patterns. For instance, house prices in Germany and Italy seem to be unaffected by the GFCy.

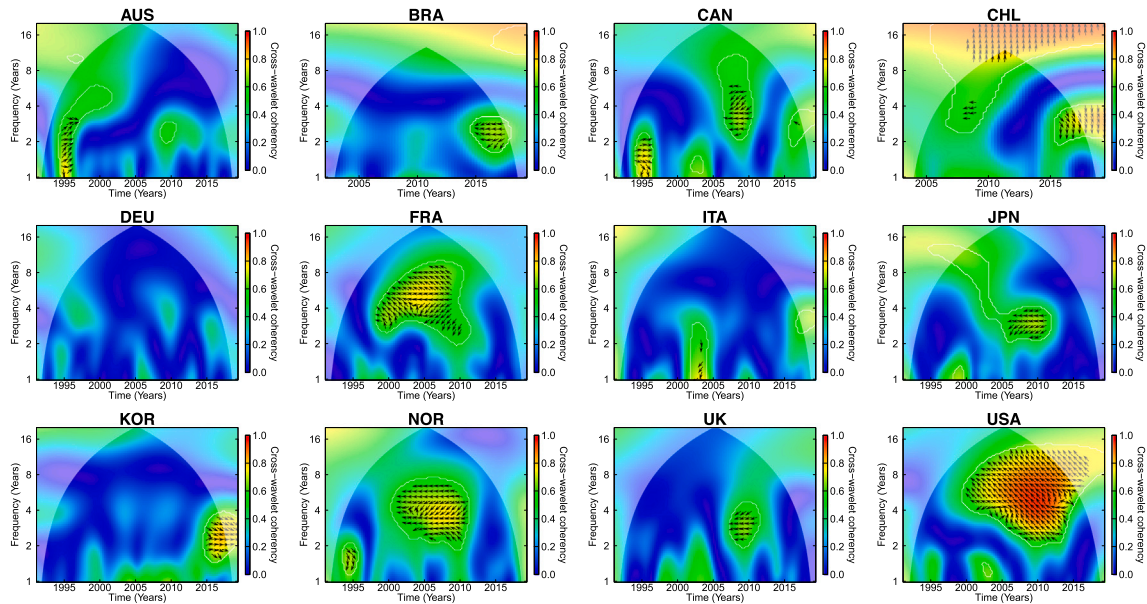


Fig. 9. Cross-Wavelet Coherency Spectra between the CBOE VIX and Real House Prices.

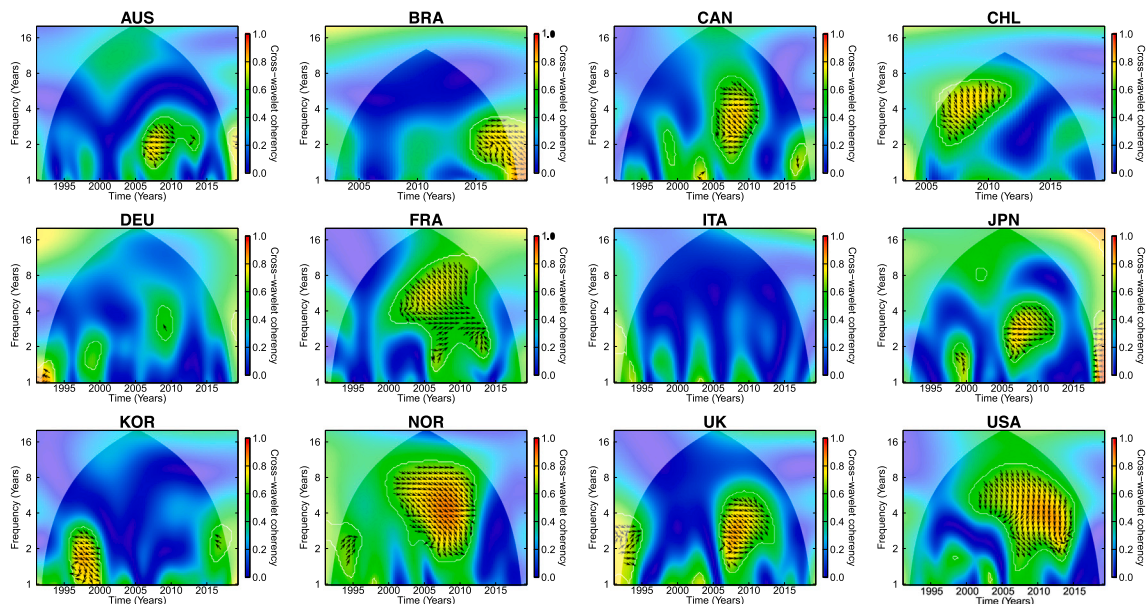


Fig. 10. Cross-Wavelet Coherency Spectra between Rey's Global Factor and Real House Prices.

These results suggest that the impact of the GFCy on house prices is much more heterogeneous than on equity prices. This is visible both in the time- and frequency-domain.

4.3. Aggregate credit: coherency and impulse responses

Similar to the responses of equity prices, our SVAR analysis indicates that the choice of the GFCy proxy is not relevant for the responses of aggregate credit either. As can be seen from Figs. 11 and 12, on impact, a GFCy shock generates an increase in aggregate credit in most countries. This effect appears significant for up to one year when considering one-standard deviation confidence intervals. The opposite is true for the US and Japan, where we observe a barely significant short-lasting negative effect on credit.

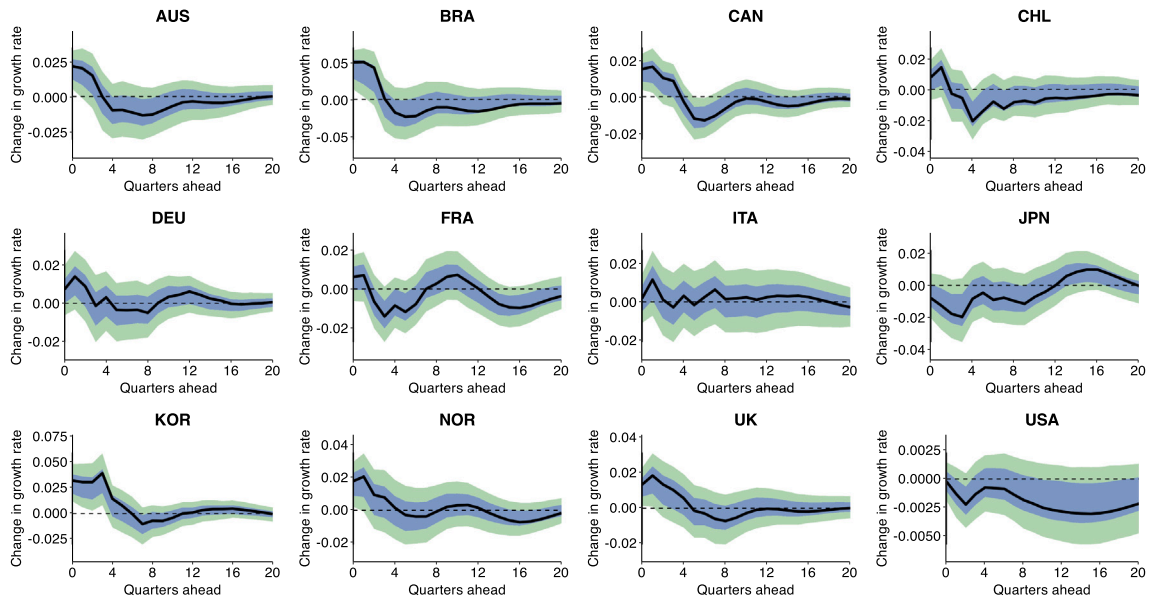


Fig. 11. Responses of Real Aggregate Credit to a negative one-standard deviation shock in the CBOE VIX. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

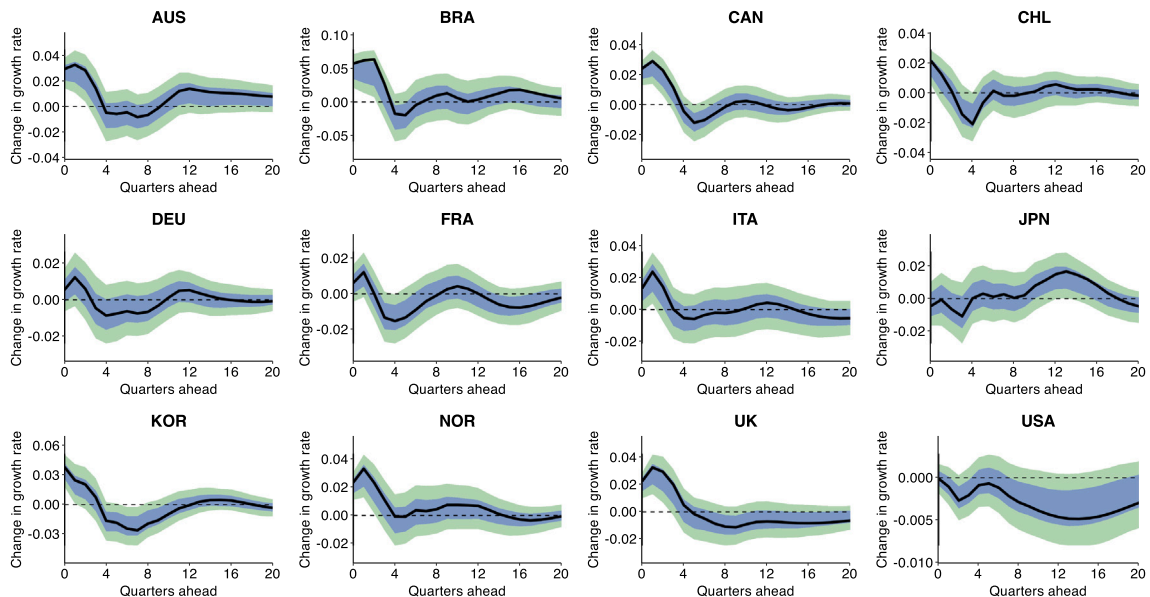


Fig. 12. Responses of Real Aggregate Credit to a positive one-standard deviation shock in Rey's Global Factor. Note: Blue and green shaded areas denote 68 % and 95 % bootstrapped error bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

The overall impression in the frequency-domain is that the relationship between the CBOE VIX and aggregate credit is limited to the occurrence of the global financial crisis for most countries (Fig. 13), and mostly at business cycle frequencies (2 to 4 years). As notable cases, the US displays coherency at very high (1 to 2 years) and medium (4 to 10 years) frequencies, while the UK exhibits coherency across all frequencies from 1 to 8 years. Furthermore, credit in Germany and France is almost unaffected by the VIX, while credit in Japan only interacts with the VIX in the mid-1990s. There is not a uniform lead-lag relationship across countries, but arrows mostly point to the left, indicating that the series are in anti-phase, or to the left and down, indicating that the VIX leads.

When Rey's global factor of asset prices is considered instead (Fig. 14), the areas of coherency become somewhat larger for most countries, except for Japan. The frequency ranges, however, remain slightly similar, particularly for the US and the UK. Once more, the global financial crisis is the event in time where cross-wavelet coherency peaks across countries. Additionally, credit in the three largest European economies (Germany, France, Italy) also interacts with the GFCy at business cycle frequencies around the start of the Euro. The lead-lag relationship is diverse across countries and episodes.

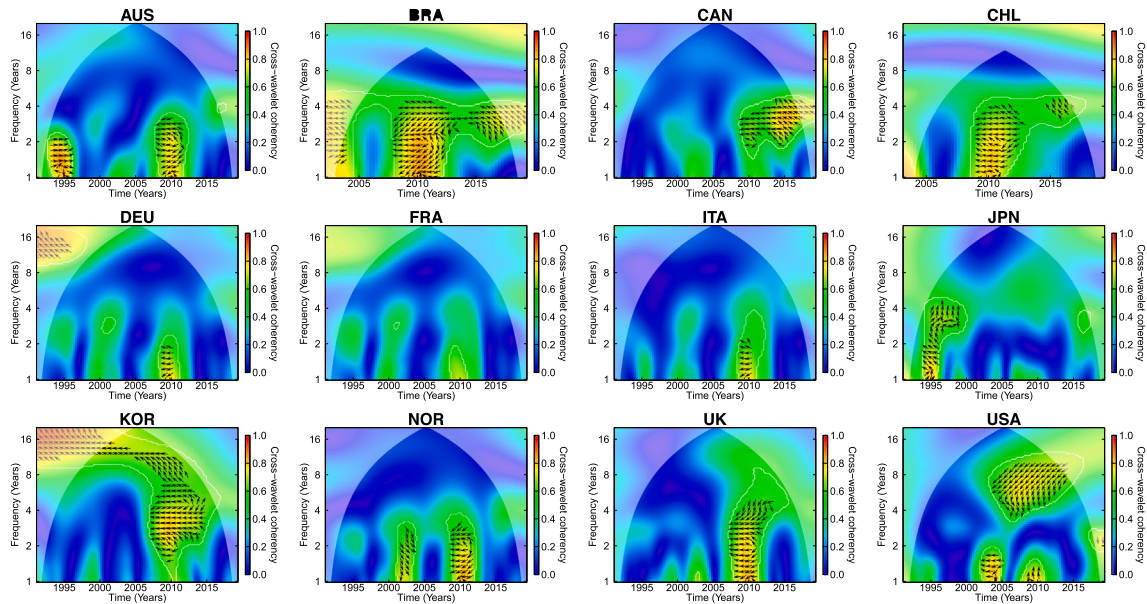


Fig. 13. Cross-Wavelet Coherency spectra between the CBOE VIX and real aggregate credit.

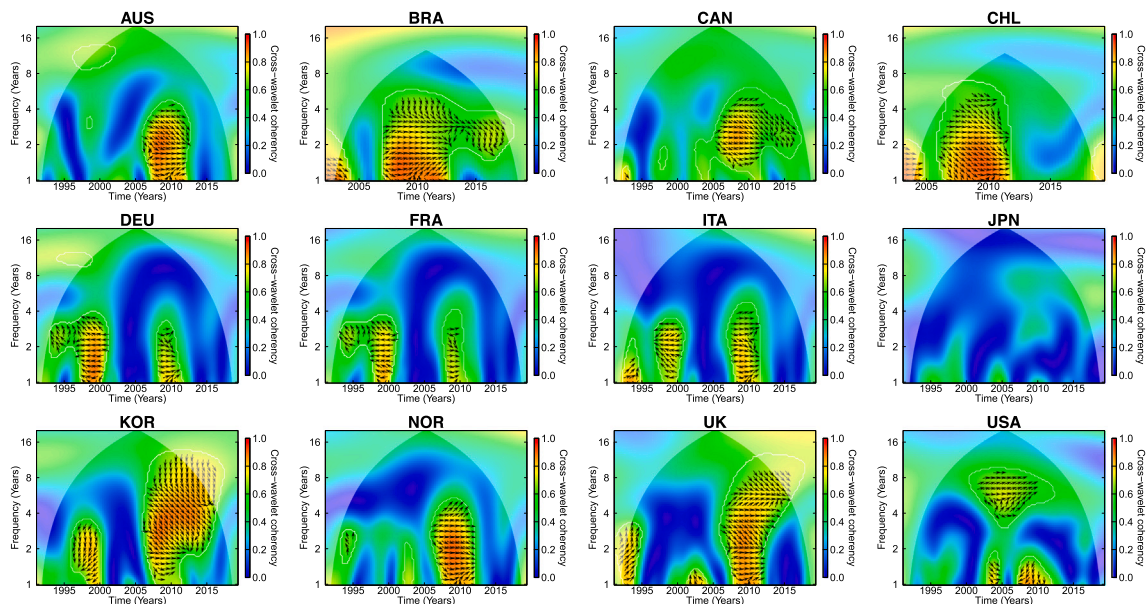


Fig. 14. Cross-Wavelet coherency spectra between Rey's global factor and real aggregate credit.

Unlike the SVAR framework, we find that the cross-wavelet coherency graphs reveal significant variations across time and frequencies for all countries.

5. Concluding remarks

Despite its relevance, the question addressed in this paper has so far only been tangentially analyzed in the literature: how strong is the link between the global financial cycle and national macro-financial dynamics?

Our study builds upon previous contributions in the frequency-domain tradition such as Strohsal et al. (2018, 2019); Verona (2016), and Mandler and Scharnagl (2022a,b), each of them with their own merits. However, we expand the literature by conducting a comprehensive analysis of the global-national interaction of the financial cycle. Yet, it is important to place our results into context of a current debate in the literature. Rey (2013) as well as Miranda-Agrippino and Rey (2015, 2020, 2022) put forward the idea of a global financial cycle (GFCy), a common factor emerging from the joint movements in the capital flows, asset prices and credit, which is correlated with the VIX, but uncorrelated with country-specific macroeconomic conditions. On the other hand, Cerutti et al. (2019) questioned the concept of a GFCy given its weak empirical manifestations, in particular with regard to capital flows. Our results sit in the middle: We do not question the existence of a GFCy as other contributions do. Instead, we present two main findings. First, the relationship between the GFCy and national financial cycles is heterogeneous across countries. The relationship varies between being very pronounced and being very weak. The heterogeneity is mostly visible in the frequency-domain. Second, the choice of the global financial cycle proxy plays a limited role only.

Specifically, our results suggest that there is not a uniform interaction between the global financial cycle and national macro-financial dynamics. In the frequency-domain, the interactions are country-specific, time-varying, and with significant similarities across countries only during periods of financial distress. Moreover, the global effects are more visible in equity prices than in house prices or credit volume. These results are not sensitive to the choice of the GFCy proxy, although we also discuss the economic significance of the choice between the CBOE VIX and Rey's global factor of asset prices. In the time-domain, on the other hand, we observe significantly less heterogeneity across countries, with the exception of house prices. The responses of equity prices to a GFCy shock are qualitatively uniform across most countries regardless of the GFCy proxy choice, while credit responds differently in the US compared to other countries (but not due to the choice of the proxy).

As the wavelet analysis allows us to explore the strength and direction of comovement across frequencies and periods of time, it reveals dynamics that would otherwise remain entangled in constant-coefficient approaches. Yet, the bivariate nature of the wavelet approach we followed in this study also comes with a cost: The structural meaning of our findings in the frequency-domain is limited. Moreover, although the SVAR models provide further context in the time-domain, only one shock has been identified. Hence, our results should be taken as a departure point for further analyses of this research question.

CRedit authorship contribution statement

Christian R. Proaño: Writing – review & editing, Visualization, Supervision, Conceptualization, Validation, Methodology, Formal analysis, Writing – original draft, Investigation. **Leonardo Quero Virla:** Writing – review & editing, Visualization, Supervision, Methodology, Data curation, Writing – original draft, Validation, Software, Investigation, Conceptualization. **Till Strohsal:** Supervision, Investigation, Data curation, Writing – review & editing, Visualization, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization.

Appendix A. Sample description

Our analyses rely on macroeconomic and financial data at quarterly frequency running from 1990 to 2019 (see Table 1 for exact dates), including 12 representative economies. The selection of countries was based on their economic importance, prioritizing those with larger GDPs and larger financial markets to ensure the representation of the key global economies. We aimed to include countries from different regions to analyze possible differences and similarities. Data availability at the time of the study further guided our choice. The selection of variables is standard with respect to the literature (see e.g., Miranda-Agrippino and Rey, 2022; Strohsal et al., 2019; Cerutti et al., 2019): as alternative measures of the global financial cycle, we consider the CBOE VIX index and Rey's global factor of risky asset prices. Further, besides GDP, we consider three variables as proxies of macro-financial dynamics, namely, equity prices, house prices, and aggregate credit following Drehmann et al. (2012), who pointed out that the core of financial intermediation should be well captured by these three series. All time series in our sample were retrieved from publicly available sources (see Table 2), with the exception of the global factor of risky asset prices from Rey (2013) and Miranda-Agrippino and Rey (2022), computed by the authors using proprietary data.

Regarding data transformations, equity prices, house prices, aggregate credit and GDP were deflated with a domestic consumer price index, and therefore our analysis addresses real magnitudes. Then, natural logarithms and annual first differences were applied to the resulting real variables.¹⁰ On the other hand, the CBOE VIX was transformed to its natural logarithm, and Rey's global factor

¹⁰ Although the continuous wavelet transform does not require the data to be stationary, we used the augmented Dickey-Fuller (ADF) and KPSS tests to explore the order of integration of the series. Considering the mixed results with the series in levels, applying annual first differences not only ensures approximately stationary time series but also provides a simple interpretation.

Table 1
Countries in the sample.

| Country | Country Code | Sample start in Wavelet analysis | Sample start in SVAR analysis |
|----------------|--------------|----------------------------------|-------------------------------|
| Australia | AUS | 1990 Q1 | 1990 Q1 |
| Brazil | BRA | 2001 Q1 | 2001 Q1 |
| Canada | CAN | 1990 Q1 | 1990 Q1 |
| Chile | CHL | 2002 Q1 | 2002 Q1 |
| France | FRA | 1990 Q1 | 1990 Q1 |
| Germany | DEU | 1990 Q1 | 1991 Q1 |
| Italy | ITA | 1990 Q1 | 1995 Q1 |
| Japan | JPN | 1990 Q1 | 1994 Q1 |
| South Korea | KOR | 1990 Q1 | 1990 Q1 |
| Norway | NOR | 1990 Q1 | 1990 Q1 |
| United Kingdom | UK | 1990 Q1 | 1990 Q1 |
| United States | USA | 1990 Q1 | 1990 Q1 |

Note: The sample ends in 2019-Q1 along with the last observation of Rey (2013)'s global factor of asset prices, updated in Miranda-Agrippino and Rey (2022). The sample start indicates the first observation in the data prior to transformations. Moreover, the samples for the SVAR analysis are slightly shorter as GDP series are shorter than the purely financial series used in the wavelet analysis.

Table 2
Raw Variables and Sources.

| Variables | Description | Source |
|-------------------------------------|---|--|
| CBOE VIX | Measures the level of expected volatility of the S&P 500 Index over the next 30 days, implied from real-time bid/ask quotations of SPX options. | FRED, St. Louis Fed |
| Rey's Global Factor of Asset Prices | Comovement of 800+ asset prices extracted from a dynamic factor model. | Rey (2013), Miranda-Agrippino & Rey (2022) |
| Equity prices | Indices of nominal equity prices. | OECD |
| House prices | Indices of nominal residential house prices. | BIS |
| Aggregate credit | Credit to private non-financial sector from all sectors at market value, US dollar (Billions). | BIS |
| GDP | Seasonally adjusted nominal GDP, domestic currency, million. | IMF |
| CPI | National consumer price index, all items. | IMF |

of risky asset prices was standardized, in line with the Strohsal et al. (2019) and Miranda-Agrippino and Rey (2022), respectively. Overall, our transformations are relatively in line with those undertaken by Verona (2016).

Appendix B. SVAR methodology

Following the exposition of Kilian and Lütkepohl (2017), consider a reduced-form VAR model:

$$z_t = A_1 z_{t-1} + \dots + A_p z_{t-p} + u_t \quad (8)$$

where $z_t, t = 1, \dots, T$ is a K -dimensional time series (being K the number of variables in the model) which can be well approximated by a VAR of order p . In our case, z_t contains the global financial cycle proxy, real GDP, real aggregate credit, real equity prices and real house prices, as specified in Section 2.2 and subject to the transformation of variables explained in Appendix A. $A_i, i = 1, 2, \dots, p$ are coefficient matrices that can be estimated consistently and efficiently by ordinary least squares. u_t is an error vector assumed to be white noise with $E(u_t) = 0$ and positive definite variance–covariance matrix $E(u_t u_t') = \Sigma_u$.

With some manipulation, the structural counterpart would be denoted by:

$$B_0 z_t = B_1 z_{t-1} + \dots + B_p z_{t-p} + w_t, \quad (9)$$

where w_t denotes a vector of mean zero serially uncorrelated error terms, also called structural shocks, assumed to be unconditionally homoskedastic unless otherwise stated. $B_i, i = 0, \dots, p$ are $K \times K$ coefficient matrices, where B_0 is the so-called matrix of contemporaneous relationships. The variance–covariance matrix of w_t is normalized such that $E(w_t w_t') \equiv \Sigma_w = I_K$. This implies that the structural shocks are mutually uncorrelated.

In practice, the most popular way of identifying B_0 is to define the lower-triangular $K \times K$ matrix P with positive main diagonal such that $PP' = \Sigma_u$. P is then the lower-triangular Cholesky decomposition of Σ_u . Therefore, from the condition $\Sigma_u = B_0^{-1} B_0^{-1'}$ it follows that $B_0^{-1} = P$ is one possible solution to the problem of obtaining w_t (Kilian and Lütkepohl, 2017). Considering that P is lower triangular, it has $K(K-1)/2$ zero parameters, and as a result, the order condition for the exact identification of the unknown parameters in B_0^{-1} is satisfied. Moreover, B_0^{-1} being lower triangular implies that so is B_0 . This approach is the so-called *recursive identification*.

In recursively-identified models, however, *orthogonalized* impulse responses are not unique and depend on the particular ordering of the variables. The *generalized* impulse response (GIRF) methodology of Pesaran and Shin (1998) attempts to circumvent this by computing impulse responses that are invariant to the ordering, directly from reduced-form residuals u_t . Specifically, the GIRF of z_t

Table 3

FEVD, 20 Periods Ahead: Share of Variance Explained by Global Financial Cycle Proxies (log CBOE VIX and standardized Rey's global factor of asset prices).

| | | Real Equity Prices | Real House Prices | Real Credit Volume |
|-----|---------------|--------------------|-------------------|--------------------|
| AUS | CBOE VIX | 0.43 | 0.16 | 0.11 |
| | Global Factor | 0.61 | 0.22 | 0.23 |
| BRA | CBOE VIX | 0.16 | 0.16 | 0.25 |
| | Global Factor | 0.34 | 0.14 | 0.34 |
| CAN | CBOE VIX | 0.44 | 0.06 | 0.19 |
| | Global Factor | 0.66 | 0.10 | 0.37 |
| CHL | CBOE VIX | 0.07 | 0.07 | 0.17 |
| | Global Factor | 0.14 | 0.11 | 0.13 |
| DEU | CBOE VIX | 0.42 | 0.02 | 0.04 |
| | Global Factor | 0.45 | 0.03 | 0.05 |
| FRA | CBOE VIX | 0.49 | 0.27 | 0.10 |
| | Global Factor | 0.42 | 0.24 | 0.10 |
| ITA | CBOE VIX | 0.37 | 0.01 | 0.01 |
| | Global Factor | 0.30 | 0.03 | 0.07 |
| JPN | CBOE VIX | 0.59 | 0.19 | 0.12 |
| | Global Factor | 0.34 | 0.05 | 0.09 |
| KOR | CBOE VIX | 0.17 | 0.04 | 0.24 |
| | Global Factor | 0.19 | 0.02 | 0.25 |
| NOR | CBOE VIX | 0.48 | 0.06 | 0.07 |
| | Global Factor | 0.49 | 0.11 | 0.16 |
| UK | CBOE VIX | 0.50 | 0.09 | 0.08 |
| | Global Factor | 0.57 | 0.22 | 0.32 |
| USA | CBOE VIX | 0.25 | 0.21 | 0.11 |
| | Global Factor | 0.50 | 0.44 | 0.25 |

at horizon h is defined by

$$GIRF_z(h, \delta_j, \Omega_{t-1}) = E(z_{t+h}|u_{jt} = \delta_j, \Omega_{t-1}) - E(z_{t+h}|\Omega_{t-1}), \quad (10)$$

where Ω_{t-1} refers to one particular history of the process z_t , while $j = 1, 2, \dots, K$ contains the elements of u_t and δ_j is an impulse to the j -th element. Hence the GIRF at $t+h$ can be interpreted as the difference between the expected value of a stochastic process conditional on an impulse δ hitting the process at time t , and the conditional expectation that is obtained without such shock. The drawback of the GIRF approach is that it drops the assumption of uncorrelated structural shocks, which can make a structural interpretation more challenging.

Pesaran and Shin (1998) showed that when the variance–covariance matrix of reduced-form residuals is non-diagonal, the Cholesky impulse response approach and the GIRF counterpart produce the same results for $j = 1$, i.e., only for a shock to the first VAR equation.

Appendix C. Forecast error variance decomposition

Following a conventional SVAR approach with recursive restrictions, where variables are ordered as specified in Section 2.2, we computed a forecast error variance decomposition for each estimated model (Table 3). The most evident finding is that the share of the variance of country-specific macro-financial variables that is explained by the GFCy shock, depends heavily on the choice of the GFCy proxy. For instance, in the US, the share of variance explained by a GFCy shock is twice larger when Rey's global factor is the selected proxy against the CBOE VIX. A similar picture is visible for the UK, while Germany, France, and Italy are more or less unaffected by the choice of the proxy.

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