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Fintech vs bank credit: how do they react to monetary policy?

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Abstract

Fintech credit, which includes peer-to-peer and marketplace lending as well as lending facilitated by major technology firms, is witnessing rapid growth worldwide. However, its responsiveness to monetary policy shifts remains largely unexplored. This study employs a novel credit dataset spanning 19 countries from 2005 to 2020 and conducts a PVAR analysis to shed some light on the different reaction of fintech and bank credit to changes in policy rates. The main result is that fintech credit shows a lower (even non-significant) sensitivity to monetary policy shocks in comparison to traditional bank credit. Given the still marginal – although fast growing – macroeconomic significance of fintech credit, its contribution in explaining the variability of real GDP is less than 2%, against around one quarter for bank credit.

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Keywords: fintech credit, monetary policy, PVAR, collateral channel.

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1. Introduction

Credit markets are undergoing a profound transformation. While traditional lenders such as banks and credit unions continue to be the primary source of finance in most economies, with capital markets also playing an important role in some cases, new intermediaries have begun to make their mark. In particular, digital lending models such as peer-to-peer and marketplace lending have seen significant growth in numerous economies over the past decade (Claessens et al., 2018). Furthermore, in more recent years, several prominent technology-driven companies (often referred as "big techs") have ventured into credit markets, providing loans to their clients either directly or in partnership with financial institutions (Frost et al. 2019). These new types of credit, enabled by online platforms and big data for assessing creditworthiness are commonly termed "fintech credit".[1]

Fintech credit is witnessing rapid global expansion, achieving macroeconomic significance in many countries including China, Korea, Malaysia, and Kenya where it reaches up to 5% of total credit (Cornelli et al., 2023). In light of this trend, it becomes essential to investigate how fintech credit responds to monetary policy and to identify the key differences in its monetary transmission mechanism relative to traditional bank credit.[2]

Three primary differences between fintech and bank credit could influence their responses to a monetary policy shock.

First, rather than relying on physical collateral to address agency issues between lenders and borrowers, the business model of fintech credit is grounded in data (Gambacorta et al., 2019). As a result, fintech credit responsiveness to asset price fluctuations triggered by shifts in monetary policy is lower (Gambacorta et al., 2022).

Second, fintech platforms may operate within regulatory frameworks distinct from those governing traditional banks, enabling them to extend credit under varied terms. Moreover, the

1 Fintech credit encompasses various innovative credit forms. This includes digital lending models such as peer-to-peer (P2P)/marketplace lending and invoice trading, all facilitated by online platforms rather than traditional banks or lending institutions. Another notable form is "big tech credit", which is credit extended either directly or in partnership with financial institutions by large firms primarily engaged in the technology sector. For simplicity in this paper we group these two alternative finance forms together, referring to both collectively as "fintech credit".

2 See De Fiore et al (2023) for a model-based analysis of the relative impact of big tech and bank credit on the transmission of monetary policy.

competitive dynamics between fintech platforms and conventional banks can shape credit offerings and their reactions to monetary policy in different ways. As traditional bank credit becomes more constrained due to monetary policy tightening, businesses could readdress their needs towards fintech platforms (Hasan et al., 2023).

Third, the superior monitoring and screening capabilities of big tech lenders render their credit scoring highly sensitive to changes in firms' transaction volumes and network scores, especially for online firms (Gambacorta et al. 2022). Therefore, any alteration in monetary policy affecting general business conditions could swiftly influence credit supply. In particular, when monetary policy is relaxed, big tech lenders are more likely to establish new lending relationships with firms than their traditional counterparts (Huang et al., 2023). This suggests that big tech credit might facilitate the transmission of monetary policy via the extensive margin relative to traditional bank loans.

In summary, while the first two differences suggest a diminished effectiveness of monetary policy through fintech credit, the latter would imply the opposite. To shed some light on which of these effects dominates, this paper utilises new data for 19 countries over the period 2005–2020 (Cornelli et al, 2023). We conduct a Panel VAR (PVAR) analysis to assess the responses of fintech and bank credit to a monetary policy shock. Our primary finding is that fintech credit exhibits a reduced (even non-significant) responsiveness to monetary policy shocks compared to bank credit.

2. Data description

The PVAR analysis is based on annual data for 19 countries over the period 2005 to 2020.[3] The interaction between monetary policy, the credit market and economic activity is analysed by means of the following variables: i) the logarithm of the property price index (pk); ii) the logarithm of real GDP (Y); iii) the logarithm of the consumer price index (p); iv) the logarithm of bank lending (L); v) the logarithm of fintech credit (F); vi) the monetary policy short term interest rate (i).

[3] Countries/geographical areas included in the analysis are: Australia, Brazil, Canada, Chile, China, Euro area, Indonesia, Israel, India, Japan, Korea, Mexico, Russia, South Africa, Switzerland, Thailand, Turkey, United Kingdom and United States. The behaviour of fintech and bank credit may vary between advanced economies (AEs) and emerging market economies (EMEs). However, due to the limited number of observations available (96 for AEs and 150 for EMEs), we are unable to perform a sample split analysis for the two groups of countries.

The property price index and the bank credit data are compiled by the BIS. The real GDP and the CPI come from the IMF, World Economic Outlook. The short term rate has been obtained from national central banks,[4] while fintech credit comes from the new dataset developed in Cornelli et al (2023).

To avoid the problem of spurious correlations, we have considered a PVAR in first differences. The summary statistics of all the variables used in the analysis are reported in Table 1.

Summary statistics[1]

Table 1

	Observations	Mean	Std dev	Min	Max
Δ Ln(property price index)	274	0.05	0.05	–0.02	0.18
Δ Ln(real GDP)	304	0.01	0.09	–0.16	0.16
Δ Ln(CPI)	304	0.03	0.03	0.00	0.10
Δ Ln(bank credit)	304	0.07	0.13	–0.32	0.46
Δ Ln(fintech credit)	304	0.38	0.73	–0.22	2.43
Δ short term rate	304	–0.23	1.56	–9.50	7.77

[1] Data winsorised at the 5th and 95th percentiles.

Sources: Cornelli et al (2023); BIS; IMF; national data; authors' calculations.

Table 2 below reports unit root Phillips–Perron tests for all variables in first differences. The null hypothesis that the variables contain unit roots is always largely rejected.

Unit root tests[1]

Table 2

	Δ Ln(property price index)		Δ Ln(real GDP)		Δ Ln(CPI)		Δ Ln(bank credit)		Δ Ln(fintech credit)		Δ short term rate	
	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value
Inverse chi-squared (38)	81.7	0.00	134.3	0.00	104.6	0.00	204.7	0.00	100.1	0.00	203.5	0.00
Inverse normal	–4.0	0.00	–7.3	0.00	–5.8	0.00	–10.3	0.00	–5.8	0.00	–10.8	0.00
Inverse logit *t*(99)	–4.1	0.00	–8.2	0.00	–6.1	0.00	–12.8	0.00	–6.0	0.00	–12.9	0.00
Modified inv chi-squared	5.0	0.00	11.0	0.00	7.6	0.00	19.1	0.00	7.1	0.00	19.0	0.00

[1] Based on Phillips–Perron tests. The null hypothesis is that all panels contain unit roots. The sample includes 19 countries over the period 2005–2020. Data winsorised at the 5th and 95th percentiles.

Sources: Authors' calculations.

[4] Based on data availability, we replace the short-term rate with the shadow rate from LJKmfa, LJK Limited. For more details see Krippner (2013).

3. The PVAR Model

We model a six-variable VAR system; all the variables, that are found to be I(0), are treated as endogenous. Therefore, the starting point of the multivariate analysis is:

$$z_{ct} = \mu_c + \sum_{k=1}^{l} \Phi_k \, z_{ct-k} + \varepsilon_{ct} \qquad c = 1, \dots, N \;\; t = 1, \dots, T$$
$$\varepsilon_{ct} \sim \text{VWN}(0,\Sigma) \tag{1}$$

where $z_{ct} = [pk, Y, p, L, F, i]$ and ε_{ct} is a vector of residuals.[5]

The deterministic part of the model includes country fixed effects (μ_c), while the number of lags (l) is set to 1.

The optimal lag selection criteria follows Andrews and Lu (2001). Table 3 below presents the results from the first-, second-, third-, and fourth-order PVAR models using the first four lags of the endogenous variables as instruments. For the fourth-order panel VAR model, only the coefficient of determination (CD) is calculated because the model is just-identified. The first-order PVAR is the preferred model because it has the smallest MBIC, MAIC, and MQIC. For a lag equal to 1 also the CD is minimized.[6] The choice of the deterministic component (constant vs trend) has been verified by testing the joint hypothesis of both the rank order and the deterministic component (so-called Pantula principle).

Before performing tests on the PVAR model, we have analysed Granger causality among the z_{ct} variables, focusing on fintech credit in particular. Granger tests verify if the *x* variable is useful in predicting the values of another variable *y*, conditional on past values of *y*, that is, whether *x* "Granger-causes" *y* (Granger 1969). This can be implemented as separate Wald tests

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5 We treat cross-sectional shocks as independent, and we do not model the transmission across borders explicitly. This assumption is aligned with the modelling approach where each country's shocks are not directly influenced by shocks in other countries contemporaneously. This simplification ensures the model's tractability and interpretability, especially given the focus on the effects on fintech and bank credit. The constraint of limited data, especially the time dimensions, further restricts our ability to adopt more sophisticated modelling techniques that could potentially capture cross-country interdependencies. For instance, methods like Global VAR (GVAR) or other multi-country econometric models which are adept at capturing such dynamics require a more extensive dataset as well as additional identifying assumptions to yield reliable estimates. For a discussion of challenges and potential biases introduced by the absence of cross-country interdependencies in PVAR models see Canova and Ciccarelli (2013).

6 While we also want to minimize Hansen's J statistic, it does not correct for the degrees of freedom in the model like the MMSC by Andrews and Lu (2001).

with the null hypothesis that the coefficients on all the lags of an endogenous variable are jointly equal to zero; thus, the coefficients may be excluded in an equation of the PVAR model.

Lag selection

Table 3

Lags	CD	J	J pvalue	MBIC	MAIC	MQIC
1	**0.86**	133.59	0.05	**–442.86**	**–92.41**	**–228.16**
2	0.97	56.13	0.92	–328.17	–87.87	–185.03
3	0.98	22.23	0.96	–169.92	–49.77	–98.35
4	0.96					

[1] The sample includes 19 countries over the period 2005–2020. Data winsorised at the 5th and 95th percentiles.

Sources: Cornelli et al (2023); BIS; national data; Authors' calculations.

Table 4 below shows the test on whether the coefficients on the lags of each variable are zero. For example, the tests that the changes in bank credit or monetary policy interest rates do not Granger-cause the change in the logarithm of the property price index are rejected at the 95% confidence level. Interestingly, while fintech credit does not Granger cause the property price index, it Granger causes CPI prices, bank credit and the short term rate. Fintech credit marginally Granger causes real GDP (p-value 0.13) also in consideration of its still limited macroeconomic impact.

PVAR Granger test

Table 4

Equation/ excluded	Δ Ln(property price index)			Δ Ln(real GDP)			Δ Ln(CPI)			Δ Ln(bank credit)			Δ Ln(fintech credit)			Δ short term rate		
	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value
Δ Ln(property price index)				0.0	1	0.91	13.2	1	0.00	1.0	1	0.32	0.1	1	0.77	13.4	1	0.00
Δ Ln(real GDP)	0.1	1	0.71				0.0	1	0.97	0.4	1	0.54	0.6	1	0.45	2.5	1	0.12
Δ Ln(CPI)	2.5	1	0.12	6.9	1	0.01				6.9	1	0.01	1.0	1	0.32	1.0	1	0.32
Δ Ln(bank credit)	7.1	1	**0.01**	109.9	1	0.00	1.3	1	0.26				2.5	1	0.12	1.6	1	0.20
Δ Ln(fintech credit)	0.0	1	0.89	2.3	1	*0.13*	3.1	1	**0.08**	6.1	1	**0.01**				3.4	1	**0.07**
Δ short term rate	4.3	1	**0.04**	8.2	1	0.00	1.0	1	0.32	6.4	1	0.01	0.2	1	0.64			
All	26.3	5	0.00	145.6	5	0.00	27.1	5	0.00	28.4	5	0.00	4.3	5	0.50	18.4	5	0.00

The null hypothesis of the test is that the excluded variable does not Granger-cause the equation variable.

[1] The sample includes 19 countries over the period 2005–2020. Data winsorised at the 5th and 95th percentiles.

Sources: Authors' calculations.

After checking for the stability of the PVAR (see Figure A1 in the Appendix), we calculate orthogonalized Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs). Orthogonalized IRFs and FEVDs may change depending on how the endogenous variables are ordered in the Cholesky decomposition. Specifically, the ordering constrains the timing of the responses: shocks on variables that come earlier in the ordering will affect subsequent variables contemporaneously, while shocks on variables that come later in the ordering will affect only the previous variables with a lag of one period.

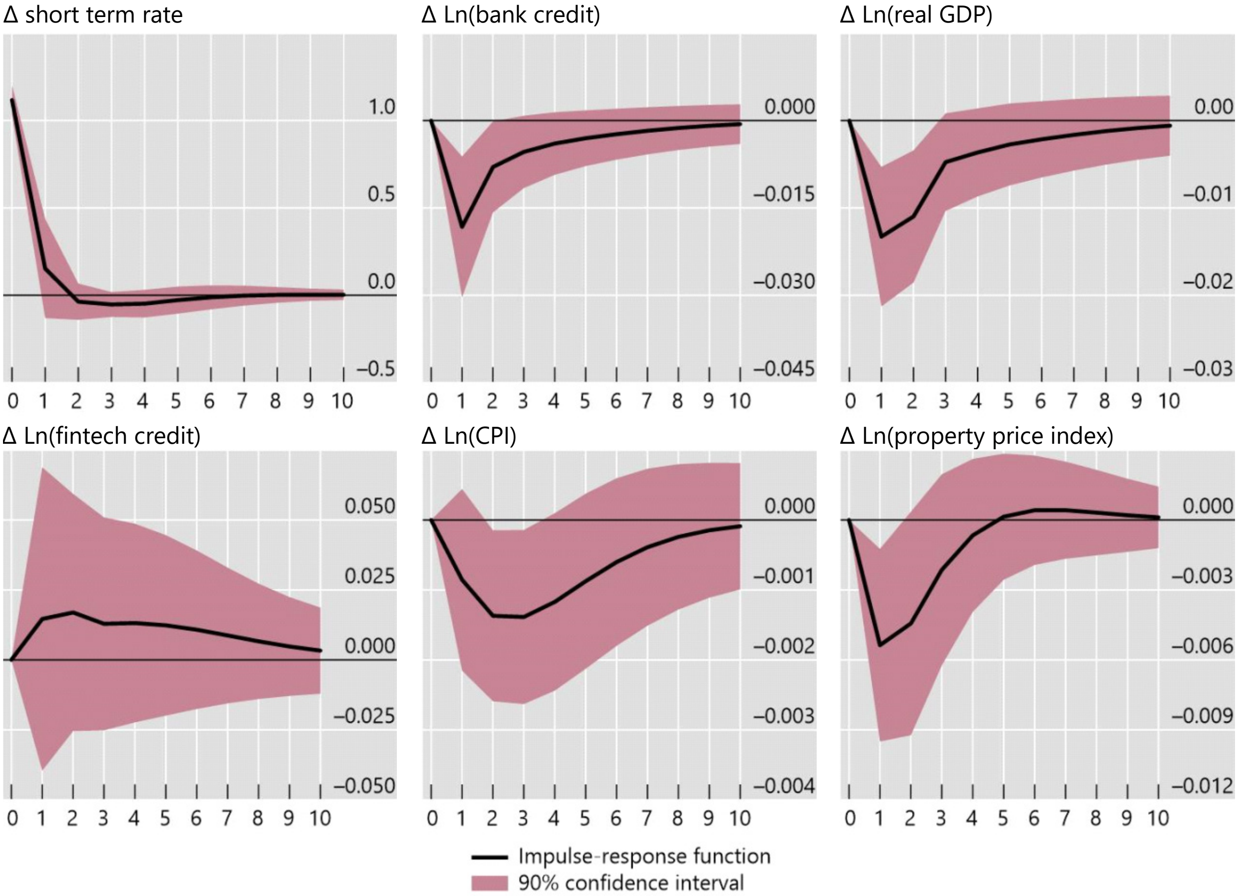
Because the ordering of variables is likely to affect orthogonalized IRFs and the interpretation of the results, in accordance with the theory, we order the variables as follows: pk, Y, p, L, F, i. The interest rate is ordered last, so it reacts to all variables within one year. This choice is guided by the literature that analyses the effectiveness of monetary policy shocks using VAR models.

Graph 1 reports the IRFs. Confidence intervals are calculated using Monte Carlo simulation with p-value bands of 90%.

The IRFs suggest that while a monetary tightening has a negative effect on asset prices and bank credit, fintech credit remains unaffected. A 1.1 percentage point increase in the monetary policy rate (top left panel) is associated with a 0.5 per cent decline in asset prices after the first year and 0.4 in the second year (bottom right panel). The effect becomes statistically not different from zero from the third year onwards, when also the interest rate returns towards the baseline. Bank credit drops significantly as an effect of the monetary policy tightening: –1.8 per cent after one year, and –0.8 per cent after two years. It also returns towards the baseline from the third year (top centre panel).

Interestingly, fintech credit is not affected by the monetary policy shocks (bottom left panel). This finding is consistent with strong substitution effects of bank credit with big tech credit in the face of a monetary tightening, as well as a limited effectiveness of the "collateral channel" on this form of credit (Gambacorta et al, 2022). The monetary tightening affects negatively real GDP (top right panel) and the CPI index. A significant effect on the price level arrives with some delay (only after one year and half) and vanishes after the third year (bottom centre panel). We compute a forecast error variance decomposition (FEVD) for the variable *Δ Ln(real GDP)* to evaluate how much of the variability of the real GDP is driven by changes in bank credit and fintech credit. The exercise in the online Appendix helps us to get a sense of the amount of information coming from each variable in the formation of real GDP (see Graph A2). While almost one quarter of real GDP variability can be attributed to the bank credit variable, fintech credit contributes only for around 2%, due to the still limited macroeconomic footprint of this form of credit in most of the analysed countries.

Impulse response functions to a monetary policy shock Graph 1



The graphs show the impulse response function for a shock in the Δ short term rate.

Source: Authors' calculations.

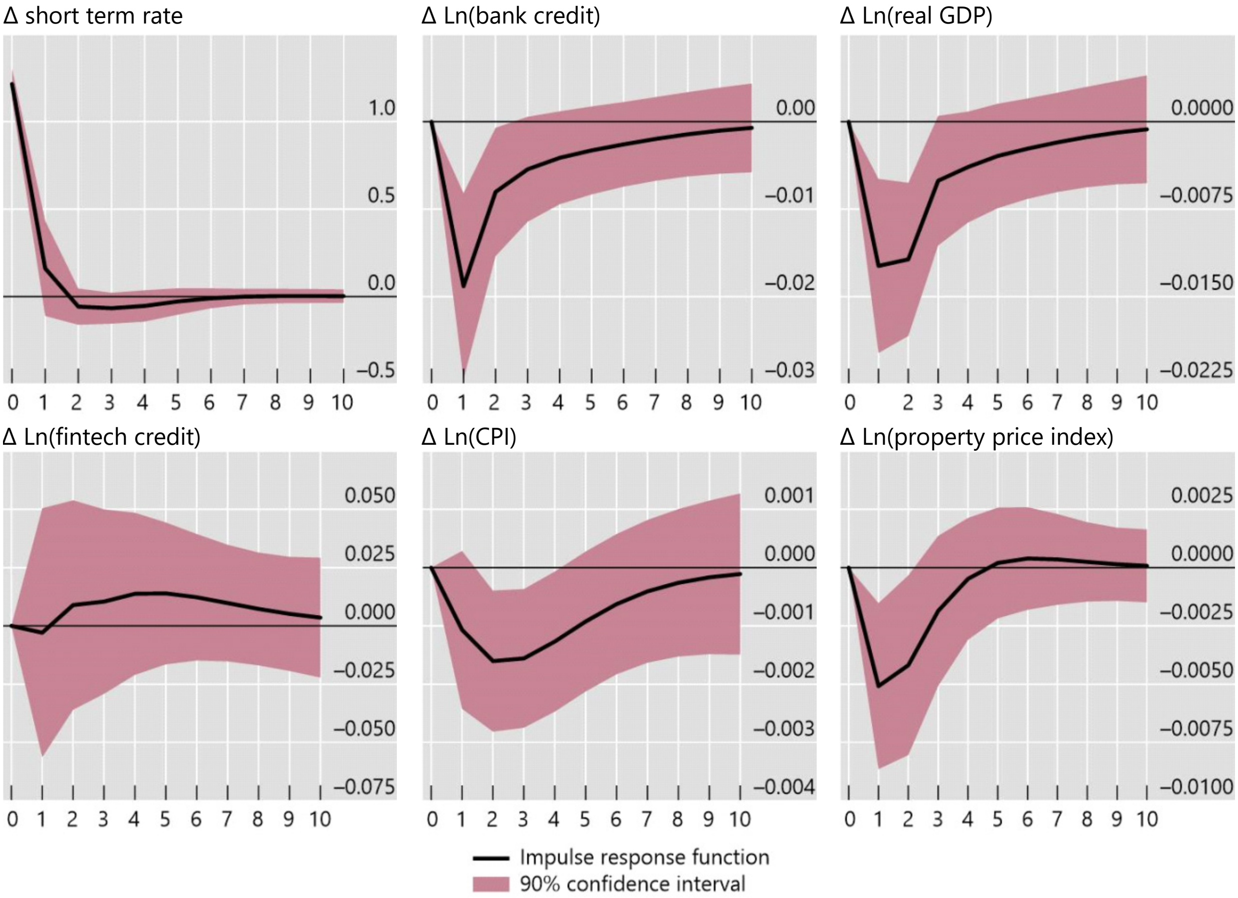
4. Robustness tests

We tested the robustness of our results in three different ways.

As a first robustness test, we swap the position of bank credit and fintech credit in the Cholesky decomposition order. The order of variables in the Cholesky decomposition is crucial because it implies a causal ordering in the response of the variables. The variable that comes first is considered to be exogenous, meaning it is not affected by the other variables contemporaneously. Each subsequent variable is treated as being affected by the preceding variables within the same time period. In other words, by swapping the position of bank credit and fintech credit in the Cholesky decomposition order we allow for fintech credit to be affected only by the lags of bank lending, but not by the contemporaneous level. Graph 2 shows the IRFs for this PVAR model.

IRFs to a monetary policy shock: change in variable's order in Cholesky decomposition

Graph 2



The graphs show the impulse response function for a shock in the Δ short term rate. The horizontal axis reports the number of steps in the simulation.

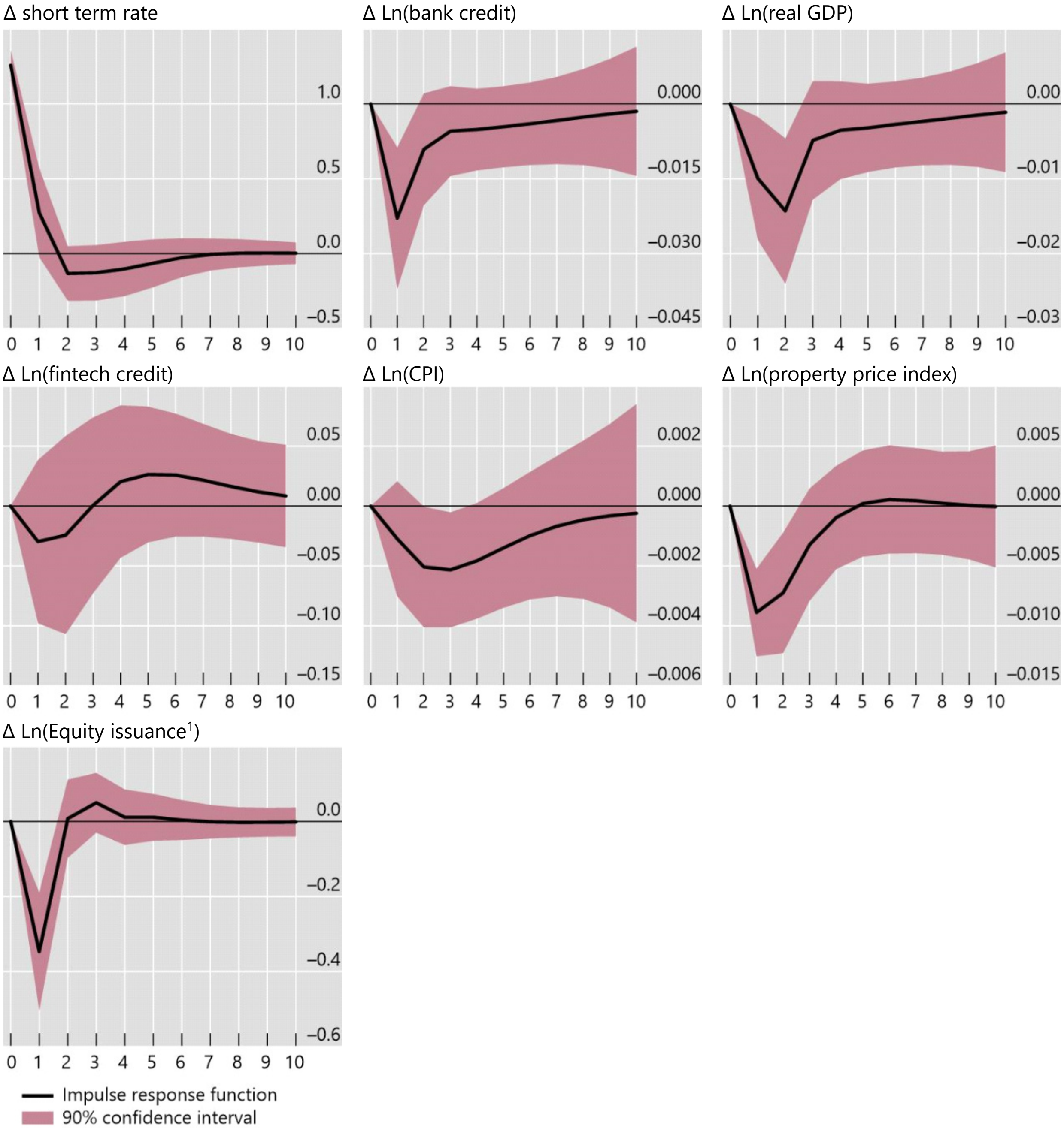
Source: Authors' calculations.

A tightenig in monetary conditions has a negative effect on asset prices and bank credit. Conversely, fintech credit remains unaffected. Similarly to the baseline case, a 1.2 percentage point increase in the monetary policy rate (top left panel) is associated with a 0.5 per cent decline in asset prices after the first year, 0.4 in the second year (bottom right panel), and an effect not statistically different from zero from the third year onwards. Bank credit drops significantly as an effect of the monetary policy tightening: –1.9 per cent after one year, and –0.8 per cent after two years. It also returns towards the baseline from the third year (top centre panel). Finally, results for CPI prices and real GDP are similar to the ones obtained in our baseline specification. Overall, these results indicate a substantial stability of the IRFs.

As a second robustness test, we augment our baseline PVAR to include the logarithm of equity issued on the stock market as an additional variable. One interpretation of our results could be that a monetary policy shock triggers a substitution effect between fintech and traditional lenders. However, some of this substitution effect could be influenced by firms' equity issuances in capital markets, an effect that the PVAR might inadvertently attribute to fintech lenders. To address this concern, we expanded our PVAR model to include an additional variable—the logarithm of equity issued on the stock market. Graph 3 shows the IRFs of this augmented PVAR model.

A 1.25 percentage point increase in the monetary policy rate (top left panel) is associated with a 0.9 per cent decline in asset prices after the first year, 0.7 in the second year (bottom right panel), and an effect not statistically different from zero from the third year onwards. Bank credit drops significantly as an effect of the monetary policy tightening: –2.3 per cent after one year. It returns towards the baseline from the second year (top centre panel). Consitently with our baseline specification, fintech credit remains unaffected. Equity issuance drops significantly in the first year after a monetary policy tightening: –35 per cent. Finally, results for CPI prices and real GDP are similar to the ones obtained in our baseline specification. Overall these results suggest that the IRF patterns remain stable even when accounting for the dynamics of equity issuance in capital markets.

IRFs to a monetary policy shock: PVAR with equity issuance Graph 3



The graphs show the IRF for a shock in the Δ short term rate. The horizontal axis reports the number of steps in the simulation.

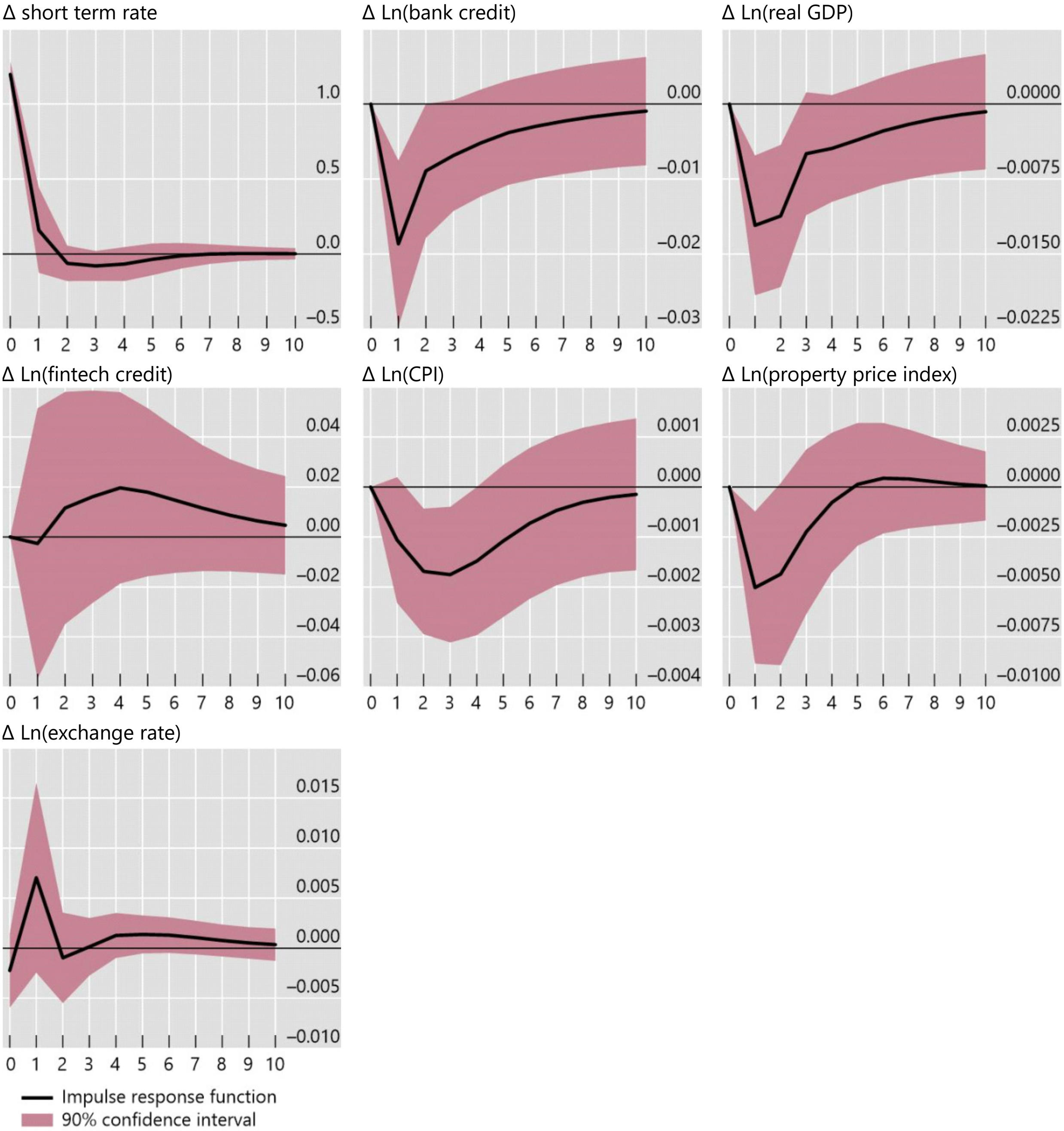
[1] Equity issuance corresponds to initial public offerings (IPO) and secondary offerings.

Sources: PitchBook Data Inc; authors' calculations.

One concern could be that if fintech lending is stronger in countries with a less developed traditional banking sector our findings could be driven by a specific group of countries. Since limited data availability does not allow us to separate emerging from advanced economies, as a third robustness test, we expand our PVAR to include the exchange rate as an additional variable to check whether it plays some role in the reaction of bank or fintech credit to a monetary policy shock. Graph 4 shows the IRFs of this augmented PVAR model.

IRFs to a monetary policy shock: PVAR with exchange rate

Graph 4



The graphs show the impulse response function for a shock in the Δ short term rate. The horizontal axis reports the number of steps in the simulation.

Sources: national data; authors' calculations.

A 1.2 percentage point increase in the monetary policy rate (top left panel) is associated with a 0.5 per cent decline in asset prices after the first year, 0.4 in the second year (bottom right panel), and an effect not statistically different from zero from the third year onwards. Bank credit drops significantly as an effect of the monetary policy tightening: –1.9 per cent after one year. It returns towards the baseline from the second year (top centre panel). Consitently with our baseline specification, fintech credit remains unaffected. The effect of a monetary policy tightening on the exchange rate is not statistically different from zero. Finally, results for CPI prices and real GDP are also similar to the ones obtained in our baseline specification. Overall these results suggest that the IRF patterns remain stable even when accounting for adjustments on foreign exchange markets.

5. Conclusions

In this paper, we use a unique credit dataset spanning 19 countries from 2005 to 2020 and undertake a PVAR analysis to elucidate the distinct responses of fintech and bank credit to monetary policy shifts. Our primary finding indicates that fintech credit exhibits a lower (and non-significant) responsiveness to monetary policy shocks when contrasted with traditional bank credit. Notably, given fintech credit's current marginal macroeconomic impact, it accounts for less than 2% in explaining the variability of real GDP, whereas bank credit contributes approximately a quarter.

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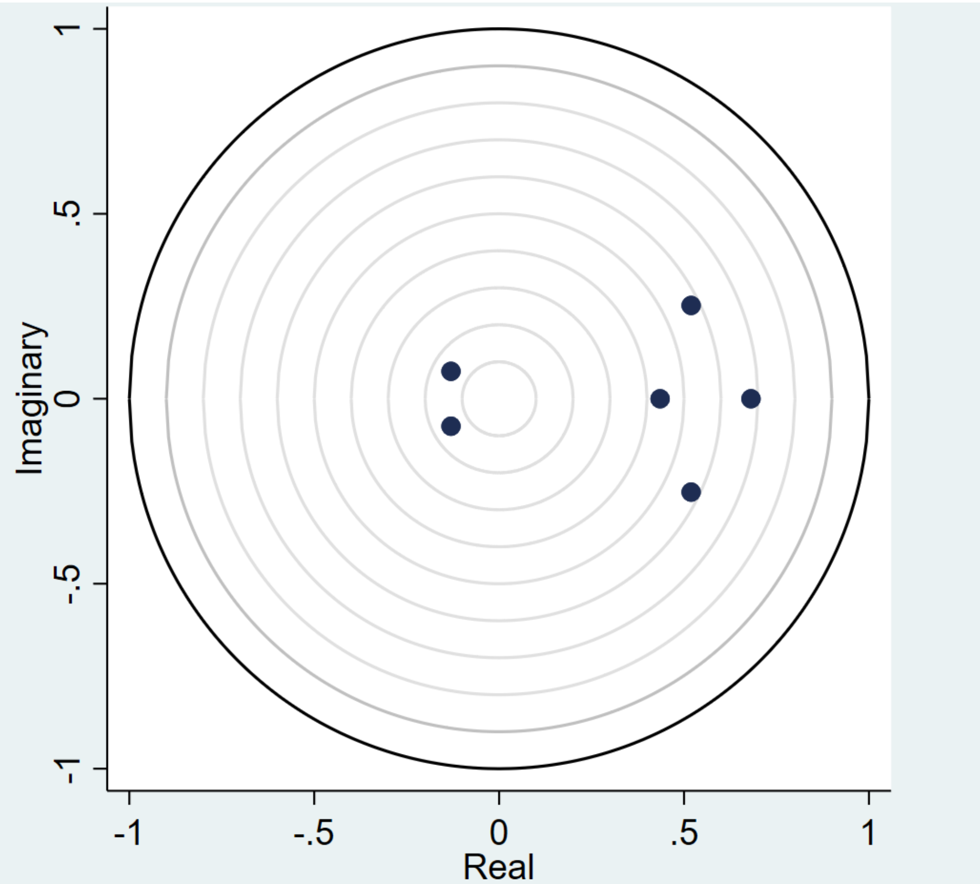
Appendix

Stability of the PVAR. The coefficients on the reduced-form PVARs cannot be interpreted as causal influences without imposing identifying restrictions on the parameters. If the fitted PVAR model is stable, it can be reformulated as an infinite-order vector moving-average (VMA) model, on which assumptions about the error covariance matrix may be imposed. Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs) have known interpretation when the PVAR model is stable. Figure A1 below shows that our PVAR is stable because all the moduli of the companion matrix are smaller than one and the roots of the companion matrix are all inside the unit circle.

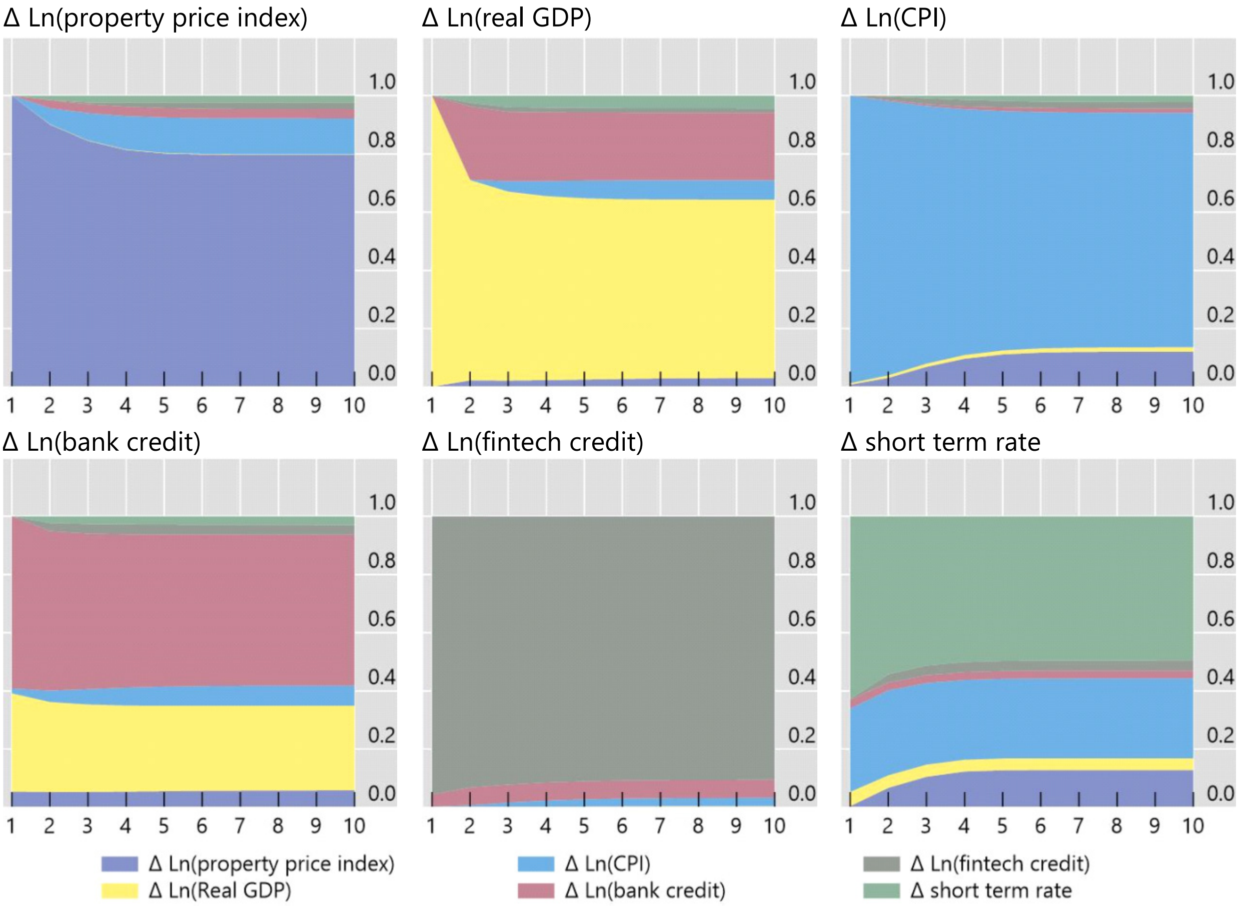
Roots of the companion matrix — Graph A1



Source: Authors' elaboration.

FVED decomposition. Graph A2 shows the forecast error variance decomposition (FEVD) that indicates how much of the variability of each variable is driven by changes in other variables. As for the contribution to changes in real GDP, while almost one quarter of the real GDP variability can be attributed to the bank credit variable, fintech credit contributes only for around 2%, due to the still limited macroeconomic footprint of this form of credit in most of the analysed countries.

Forecast-error variance decomposition — Graph A2



The graphs show the forecast-error variance decomposition. The response variable is indicated in the panel title and the impulse variable in the legend. The horizontal axis reports the number of steps in the simulation.

Source: Authors' calculations.

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