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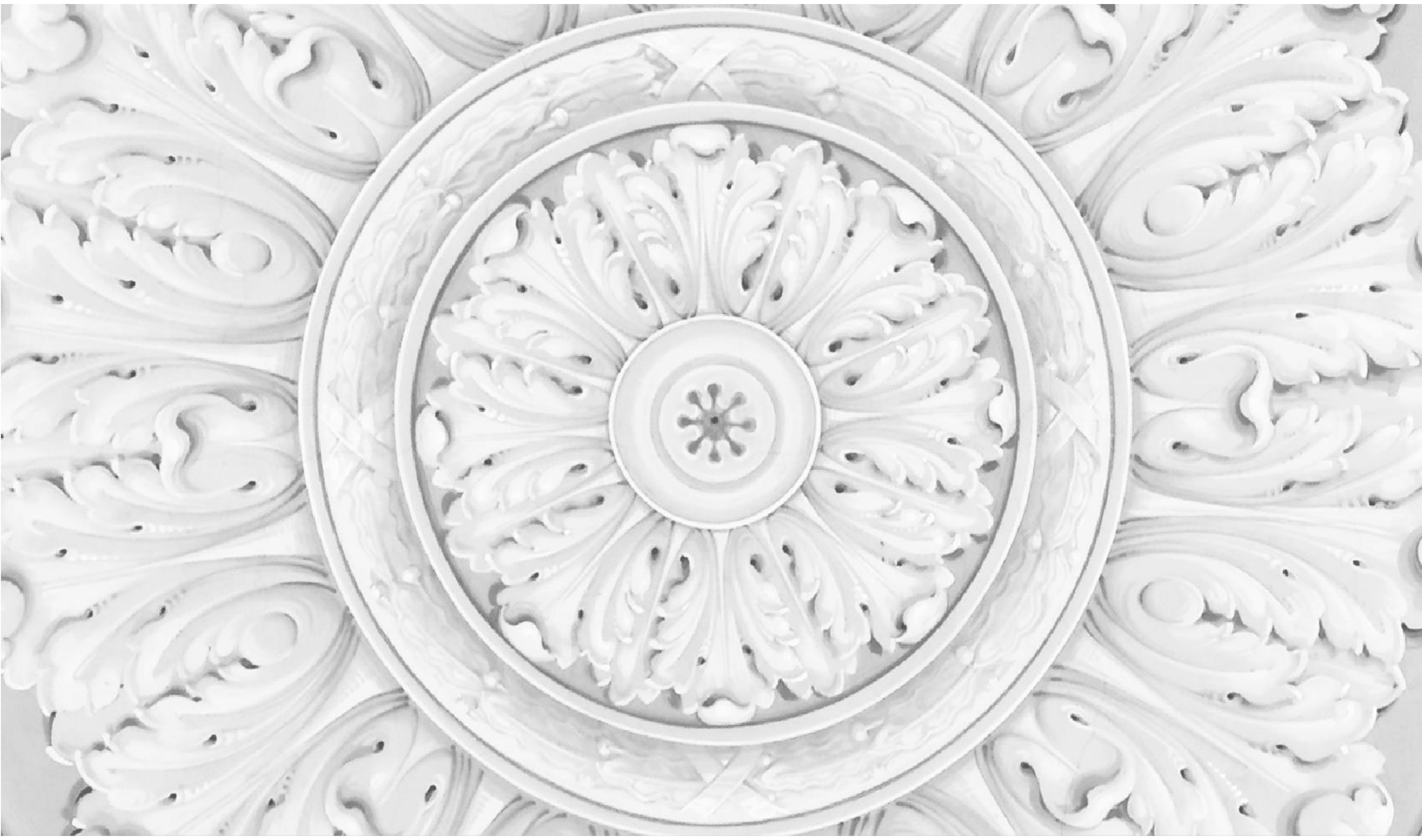

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Macro-financial linkages: the role of liquidity dependence

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Summary

We estimate a panel Bayesian vector autoregression model for a cross-section of seven advanced European economies and produce out-of-sample forecasts of GDP conditionally on observed developments of interest rates and credit. We show that, by using a smooth transition version of the model and allowing the parameters to vary across economies conditionally on their liquidity dependence (i.e. dependence on the availability of funding from external sources), it is possible to improve the accuracy of the forecasts. We conclude that the degree of liquidity dependence is likely to be among the important predictors of heterogeneity in macro-financial linkages across countries.

Key words: liquidity dependence, macro-financial linkages, Smooth Transition Bayesian VAR.
JEL-classification: G2, O16, C32.

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INTRODUCTION

The Global Financial Crisis (2007-2009) has shown the importance of understanding the linkages between financial sector and real economy. Ample research was done to study the sources and role of macro-financial linkages (see e.g. BCBS (2011, 2012), Morley (2016), Claessens and Kose (2017) for the surveys of recent literature). Notably, the shocks driven by the financial variables were found to have heterogeneous effects across both time and countries. For example, Prieto et al. (2016) found that financial shocks, especially credit shocks, contribute more to the explanation of US GDP growth fluctuations during financial crises and less during the normal times. Bijsterbosch and Falagiarda (2015) and Silvestrini and Zaghini (2015) obtain similar results for the euro area. Some of the recent literature on macro-financial linkages has shown the existence of cross-country heterogeneity in the transmission of financial shocks. As such, Guarda and Jeanfils (2012), Hubrich et al. (2013) and Bijsterbosch and Falagiarda (2015) conclude that real effects of the credit shock differs across European countries. Asset price shocks were also found by Chirinko et al. (2008) to have heterogeneous real effects across 11 EU countries, Japan, and the US.

Another strand of literature gives us good reasons to believe that heterogeneity in macro-financial linkages across economies may be associated with their industrial composition. More specifically, there is ample evidence that more financially dependent industries perform relatively worse during the contractionary phases of credit cycles (Braun and Larrain 2005; Kroszner, Laeven, and Klingebie 2007; Dell'Ariccia, Detragiache, and Rajan 2008; Abiad, Dell'Ariccia, and Li 2011). We contribute to this strand of research in several ways.

Firstly, we compile a dataset of various directly measured industry-level liquidity dependence indicators. Namely, these are ratios of inventories, current assets, labour costs and current debt to turnover (as in Raddatz 2006) as well as the benchmark indicator of external dependence (Rajan and Zingales 1998). Unlike in previous studies, we measure the liquidity dependence of all economic activities (not just manufacturing). We report our findings for 35 industries across European countries during 1999–2014. We also construct country-level aggregate liquidity dependence indicators.

Secondly, we do not limit our study to an analysis of one-off events (e.g. financial crises or recessions) but implement a more general (and arguably more practical) econometric approach. Namely, we set up a panel version of the Bayesian vector autoregression (BVAR) model as suggested by Giannone, Lenza, and Primiceri (2015) for a cross-section of seven advanced European economies and develop the smooth transition modification of the model using the liquidity dependence indicators as transition variables. The impulse responses indicate that there is significant difference in the parameterizations obtained for models describing economies with high and low liquidity dependence. Presumably, this set-up may be helpful in accounting for cross-country differences in macro-financial linkages that arise due to the variation in the degree of liquidity dependence (or other correlated factors). We test this proposition by calculating the out-of-sample forecasts of output conditionally on observed developments of financial variables. Namely, we conduct an out-of-sample forecasting exercise employing the 'leave-one-out' strategy (i.e. we estimate our models using all countries but one and make a forecast for the omitted country in a round-robin fashion) as well as a conventional recursive forecasting exercise over an expanding time sample. We find that the smooth transition model that utilizes the current assets to turnover ratio as the liquidity dependence indicator outperforms the linear version. In fact, the panel model that takes into account information on the cross-country variation of liquidity dependence outperforms country-specific BVARs. Arguably, these findings confirm the relevance of liquidity dependence indicators for a macro-financial linkage analysis.

The rest of the paper is structured as follows. Section 1 discusses the theoretical reasoning behind the linkages between liquidity dependence and output. Section 2 outlines the set-up of the empirical model. Section 3 describes the construction of alternative liquidity dependence measures. Section 4 presents the impulse-response analysis and the results of the out-of-sample forecasting exercise. Section 5 concludes.

1. THEORETICAL BACKGROUND

This section provides some theoretical foundation for the link between the degree of liquidity dependence and output during the different phases of the credit cycle.

Due to the presence of credit market imperfections, financial shocks can have amplification effect on output. The baseline literature provides several theoretical explanations for possible channels of influence. One strand of literature focuses on the, so called, balance sheet channel, in which the existence of asymmetric information (moral hazard, cost of state verification, lack of collateral) implies the firm's net worth to be the main limiting factor in the amounts of external funds available for a firm to borrow (Bernanke and Gertler (1989, 1990), Bernanke, Gertler, and Gilchrist (1999), Kiyotaki and Moore (1997)). Thus, a shock that negatively affects firm's wealth (i.e. balance sheet) limits the access to external financing, which, consequently, reduces firm's investment and production. Another strand of literature considers the effect of banks' credit supply on the output, called the bank lending channel. According to these models, a negative shock that affects the ability of banks to give loans decreases firms' operating activity, consequently, reducing output (Bernanke and Blinder (1988), Holmstrom and Tirole (1997), Stein (1998)). Most of the theoretical models above consider long-term investments, but the same reasoning can be well applied to short-term investment. Since we are dealing with changes in output during the different phases of credit cycle, focusing on short-term investments, like investments in working capital, is more applicable as fixed assets investment are known to be infrequent and large (Caballero et al. (1995)).

Theoretical literature on the link between financial frictions and business cycles is essential for developing a foundation for liquidity dependence and output during booms or busts of credit. The underlying idea is that financial shock influences the economy's output through firms' investment and production decisions, which are constrained due to the presence of credit market imperfections. In particular, contractionary financial shock limits the amount of borrowing funds available to a firm to finance its operations due to the existence of credit constraints. This lead to a reduction in the amount invested in working capital and, subsequently, the firm's production. The degree of output change depends on the firm's liquidity need, that is, the relative importance of investment in working capital. In the case of negative shock, output losses are higher the more the firm is dependent on external financing (Braun and Larrain 2005). This effect extends to the aggregate output of the economy. In this way, the degree of liquidity dependence of the firm and, consequently, of the economy may amplify the shock in the financial sector.

We provide a simple theoretical model in the spirit of Raddatz (2006), first, to show the role of liquidity dependence in a firm's optimal investment and output decision (Annex A1) and, second, to examine the magnitude of output change in response to financial shock in economies with different levels of liquidity dependence, that is, to check the hypothesis that economies with high liquidity dependence are hit harder when negative financial shock occurs (Annex A2). We consider a discrete time model with two economies populated by a continuum of two-period-lived firms. Firms' degrees of liquidity dependence (high or low) are the same within each economy, but differ between the two economies. In the first period, each firm gets some amount of cash flow and decides how much to invest in working capital to produce in the second period, according to the CES production function. We assume an imperfect credit market, in which firms can invest no more than a fixed multiple of their cash flows. In contrast to the framework provided by Raddatz (2006), which specifies this multiple as a financial development parameter, we redefine it as an access to external financing. In our model, each firm can experience a good or bad period in its cash flow. In a good period, a firm is financially unconstrained, whereas a bad period implies a firm being financially constrained. Since investment decisions occur only in the first period, proportions of firms in good and bad states are predetermined, as are both economies. Liquidity dependence is defined as the relative importance of working capital in production for each firm. To simplify the further examination of the effect of financial shock, we assume that both economies are at their steady state levels of output that are equal. We fix the amount of physical capital on different levels for each type of firm in each economy to satisfy the above assumption. Solutions to firms' optimization problems and the resulting optimal aggregate outputs for each economy are derived in Annex A1.

Within our framework, we introduce change in access to financing as a financial shock to check the above hypothesis of a relatively profound effect on output change in the economies with high liquidity dependence. According to our model, a decrease in access to financing reduces the amount of external funds available for financially constrained firms, which negatively affects their investments in working capital and, consequently, production, thus, lowering the aggregate output. Under some reasonable parameters, the negative effect on aggregate output is greater the higher the liquidity dependence of the economy. Thus, economies with high liquidity dependence are hit harder when access to financing is reduced. Detailed proof is provided in Annex A2.

We therefore conclude that the degree of liquidity dependence is likely to be among the important factors that shape macro-financial linkages in an economy.

2. MODEL SPECIFICATION

We employ the modelling strategy outlined in Banbura, Giannone, and Reichlin (2010) and in Giannone, Lenza, and Primiceri (2015). This approach, developed specifically to address the 'curse of dimensionality' and prevent the model's overfitting, is known to produce adequate results even when used for the relatively short time samples. We modify the model to accommodate the smooth transition approach that presumably may be helpful in capturing the heterogeneity in macro-financial linkages across countries. Accordingly, our main econometric tool is a panel Smooth Transition Bayesian VAR (ST-BVAR) of the form:

$$Y_{i,t} = \left(1 - z_{i,t-1}^{\alpha}\right)\left(c^1 + B_1^1 Y_{i,t-1} + \cdots + B_p^1 Y_{i,t-p}\right) + z_{i,t-1}^{\alpha}\left(c^2 + B_1^2 Y_{i,t-1} + \cdots + B_p^2 Y_{i,t-p}\right) + e_{i,t}$$

$$e_{i,t} \sim N(0, \Sigma)$$

where $Y_{i,t}$ is the vector of macroeconomic variables in country *i* in period *t*, $z_{i,t}$ is the transition variable in country *i* in period *t*, $e_{i,t}$ is the vector of errors in country *i* in period *t*, c^k is the vector of intercepts in state *k*, B_l^k is the matrix of parameters with depth *l* in state *k*, Σ is the covariance matrix, α is the hyperparameter related to curvature of transition variable influence, and p is the number of lags in the model.

The prior distributions of parameters are set as suggested in Giannone, Lenza, and Primiceri (2015). We combine Minnesota prior, 'sum-of-coefficients' prior and 'dummy-initial-observation' prior, using the vector of hyperparameters from Giannone, Lenza, and Primiceri (2015). Following Giannone, Lenza, and Primiceri (2015), we set the model lag length p = 5.

Aggregate liquidity dependence measures (constructed as described in the next section and interpolated from annual to quarterly frequency) are used as transition variables $z_{i,t}$. Note that this variable is already normalised to take values between 0 and 1. Therefore we do not need to employ a logistic specification of the transition function as in González, Terasvirta, and Van Dijk (2005). We impose Gamma prior distribution with unit mode (implying linear transition between regimes)[1] and standard deviation, which was arbitrary set to 0.1, on α.

The vector of macroeconomic variables contains four main real and financial indicators:

- GDP
- Consumer price index (CPI)
- Long-term interest rate
- Credit

All variables (except interest rate) are in log-levels and seasonally adjusted. We use quarterly data from the OECD database. The time sample and selection of countries in the cross-section (Table 1) are determined by data availability (primarily by the contents of the BACH database that is used to construct liquidity dependence indicators as described in the next section). Note that we use the cross-section comprising only advanced economies for our benchmark model, although we report the impulse responses obtained using the full cross-section in Annex C.

Table 1. Cross-section of countries and time samples

Country	Time sample
Advanced economies	
Austria	1999Q4 – 2014Q4
Belgium	1999Q4 – 2013Q4
France	1999Q4 – 2014Q4
Germany	1999Q4 – 2013Q4
Italy	1999Q4 – 2013Q4
Portugal	1999Q4 – 2013Q4
Spain	1999Q4 – 2013Q4
Emerging market economies	
Czech Republic	2000Q2 – 2014Q4
Poland	2001Q1 – 2014Q4
Slovak Republic	2006Q1 – 2014Q4

[1] The mode of posterior distribution of α also does not imply notable nonlinearity in transition between regimes.

3. MEASURES OF LIQUIDITY DEPENDENCE

We follow Raddatz (2006) in our choice of liquidity dependence (LD) indicators, namely the benchmark indicator of external dependence (ED) proposed by Rajan and Zingales (1998). It is calculated as one minus the ratio of cash flow from operations to capital expenditures.

In addition, we use the ratio of inventories to net turnover (INV). As pointed out by Raddatz (2006), this captures the fraction of inventory investment that can be typically financed with ongoing revenue. A higher value of this ratio means that a smaller fraction of inventory investment can be financed by ongoing revenue and therefore represents a higher level of external liquidity needs.

Although Raddatz (2006) argues that among the components of a firm's liquid assets inventories are particularly suitable for capturing the technological aspect of liquidity needs, we also examine the performance of an alternative indicator: the ratio of all current assets to net turnover (CA).[2]

Two other alternative indicators are the employee expenses over gross value added (WAGE), which measures the ability of a firm to finance its ongoing labour costs from its ongoing income, and the ratio of current debt to net turnover (STD), which implicitly captures both the actual use of external liquidity and the ability of a firm to pay its current liabilities out of its sales revenue.

We use the BACH database as our data source. It contains industry-level aggregates of the aforementioned indicators.[3] Our dataset includes 35 sub-aggregates[4] for 10 European countries averaged over a country-specific time sample (reported in Table 1). The data descriptive statistics are reported in Table 4 in Annex B.

In our modelling framework we cannot work directly with industry-level aggregates (mainly due to the unavailability of industry-specific credit and interest rates variables). We therefore construct aggregated country-level LD indicators in the following way:

- We rank the collection of all economic activities from all countries by one of the LD measures (INV, CA, WAGE, STD or ED).
- We label industries with LD measures above a threshold percentile (we test 50th, 66th and 75th) as 'liquidity dependent' industries. Consequently, we do not assume that an economic activity of a given type is liquidity (in)dependent across all countries but take

[2] See e.g. Subramaniam et al. (2011) and Bigelli and Sánchez-Vidal (2012) for the discussion on the link between industry-specific factors and corporate cash holdings.
[3] Therefore, unlike most other studies, we rely on directly measured indicators instead of assuming that the liquidity dependence across industries is the same as in the observed benchmark country (usually the US).
[4] We use single-digit section level disaggregation, although the manufacturing section (C) is further separated into two-digit divisions (we aggregate some of the divisions using the weights based on total assets of reported companies to match UNIDO data that is used as further described in this section).

into account the differences in observed liquidity dependence indicators. We always count financial and insurance activities (section K) as 'liquidity dependent'.

- We calculate the country-specific shares of value added produced in 'liquidity dependent' industries using annual data from the UNIDO database.[5] The time variation of our liquidity dependence indicators is, therefore, determined by changes in a country's GDP industrial composition.
- This gives us 12 sets of aggregate LD indicators (based on four alternative LD measures and three threshold percentiles). We normalize the indices in each set to take values between 0 and 1 (where 0 corresponds to a set-specific minimum and 1 to a set-specific maximum).

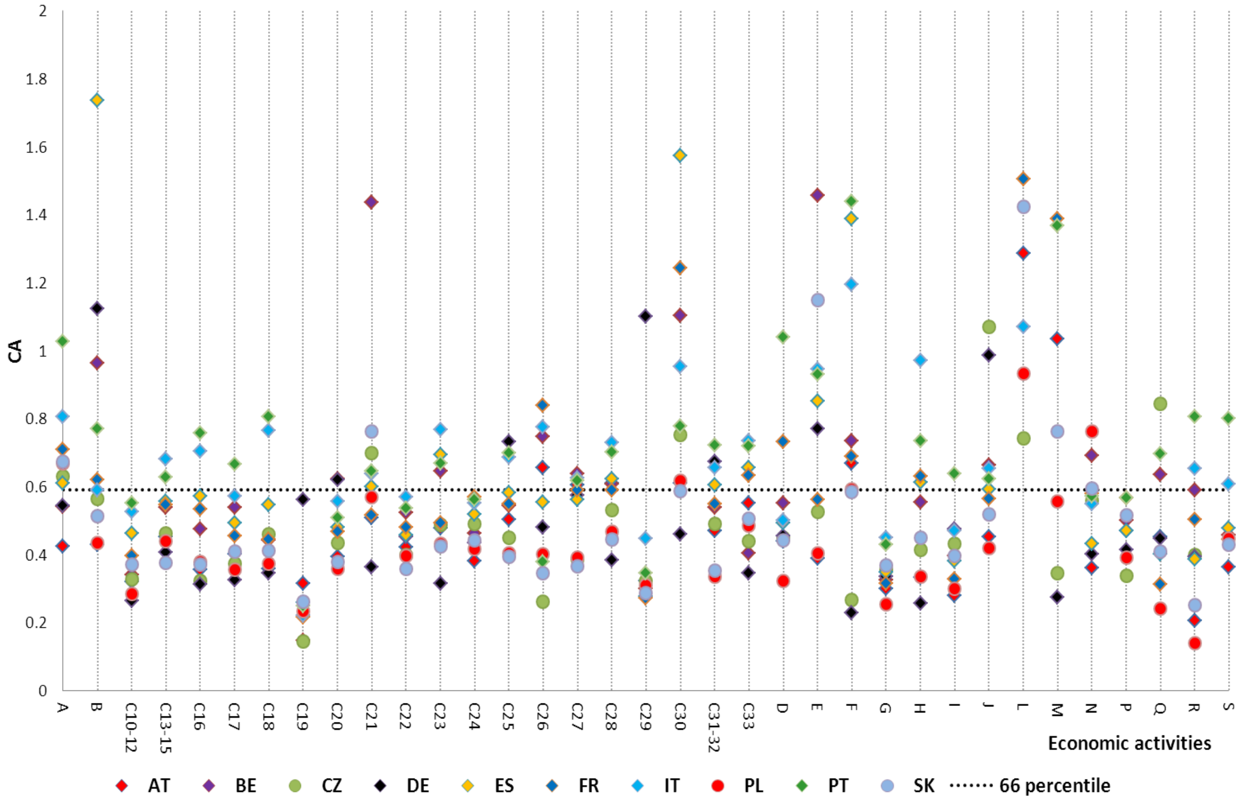
Let us examine in more detail the variation of one of the liquidity dependence measures across industries and sample countries. Figure 1 shows the average current assets ratio (CA)[6] for each industry and country of our sample for the considered time period. Using a 66th percentile threshold (dotted line), we define an industry as being liquidity dependent if its CA ratio lies above this value. There exists a significant variation across countries and industries. Portugal and Italy appear to have the largest number of liquidity-dependent economies (more than half of all industries have a CA indicator above the threshold), followed by Belgium and Spain, while Austria and Germany are the least dependent among advanced countries. Several industries (such as retail (G), education (P), food (C10–12), part of chemical (C22) and oil refining (C19) industries) appear to have consistently low ratios of current assets to sales across all counties, while the real estate industry (L) appears to be highly liquidity dependent. More detailed information on countries and industries that were classified as liquidity dependent can be found in Table 5 in Annex B.

We proceed by constructing the (not normalized) aggregate LD indicators (Figure 2), which takes into account the shares of value added produced in liquidity-dependent industries.

[5] We have also constructed indicators based on shares of employed in the industry and found the obtained indices to be highly correlated with measures based on value-added shares.

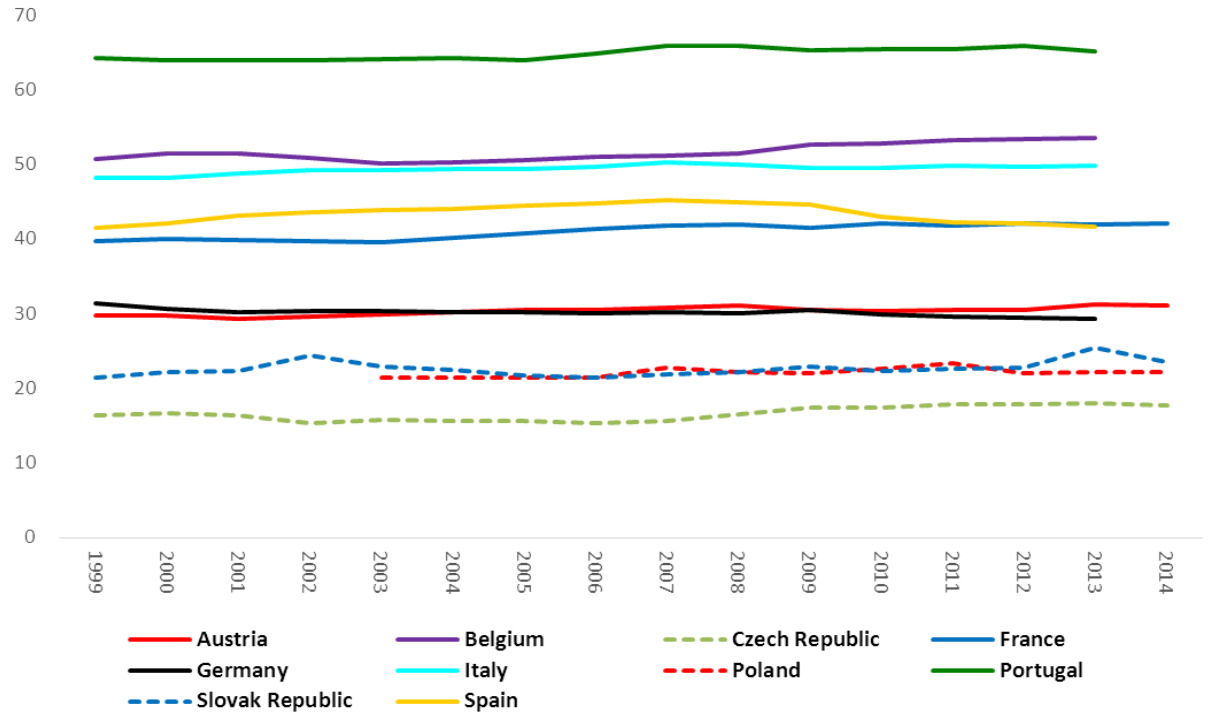
[6] We choose this variable with foreknowledge as the results reported in Section 5.2 indicate that this is the best performing indicator in terms of predicting macro-financial linkages.

Figure 1. Current assets to net turnover ratios across countries and economic activities



The CA indicators for 'L' economic activities in Germany, Portugal and Spain and for 'M' economic activities in Belgium and Spain take values from 3 to 10 and are not plotted on the chart above.

Figure 2. Aggregate liquidity dependence indicators based on current assets ratio across countries



The average values of aggregate LD indices are reported in Table 6 in Annex B. It appears that irrespective of the LD indicator employed, emerging market economies are found to be generally less liquidity dependent than advanced economies. Among advanced economies, Spain and Portugal are classified as highly liquidity dependent in accordance with the majority of alternative measures. In general, however, there is little consistency across alternative LD measures. We therefore rely on empirical results to select the most relevant indicator.

4. EMPIRICAL RESULTS

4.1. Impulse responses analysis

We estimate the empirical model outlined in Section 2 using aggregate LD indicators calculated as discussed in Section 3 as transition variables. For brevity, we only report the results obtained using transition variables based on the CA indicator (threshold is the 66th percentile) found to have the best empirical properties (see Sub-section 4.2). The impulse responses are estimated using a recursive Cholesky identification scheme with the variables' ordering as presented in Section 2. The impulse responses to these shocks in economies with high and low liquidity dependence (i.e. when the transition variable equals 1 and 0, respectively) are presented in Figures 3–6.

The detailed identification and interpretation of shocks are beyond the scope of this paper. Nevertheless, the main unambiguous observation that can be made based on the presented results is that there is noticeable difference between the two sets of impulse responses, implying that two distinctly different sets of coefficients are used to describe economies with high and low liquidity dependence. Namely, judging by the magnitude of most responses, it appears that highly liquidity-dependent economies were more sensitive to the prevailing economic shocks.[7]

In the Sub-section 4.2, we further test the extent to which the smooth transition aspect of the model may account for differences in heterogeneity of macro-financial linkages across countries.

[7] In Annex C we check the robustness of this finding for the inclusion of emerging market economies to the cross-section.

Figure 3. Impulse responses to innovation in GDP (the median and the 16th and 84th quantiles of the distribution)

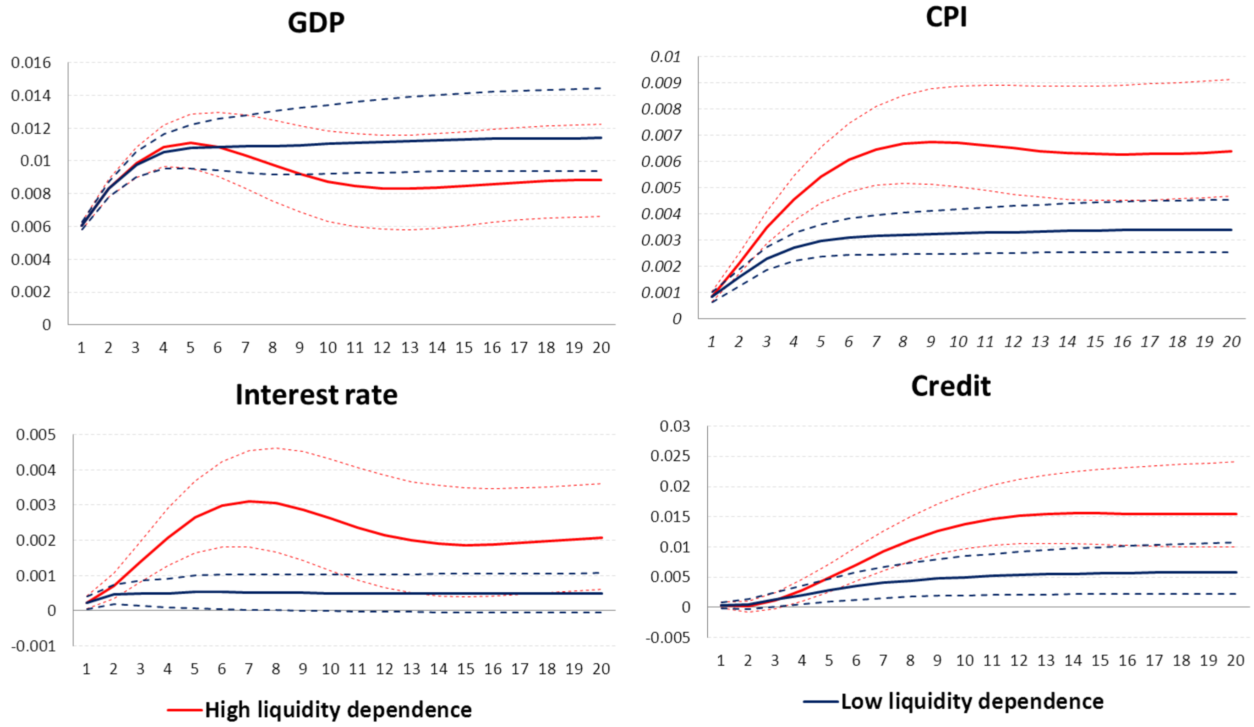


Figure 4. Impulse responses to innovation in CPI (the median and the 16th and 84th quantiles of the distribution)

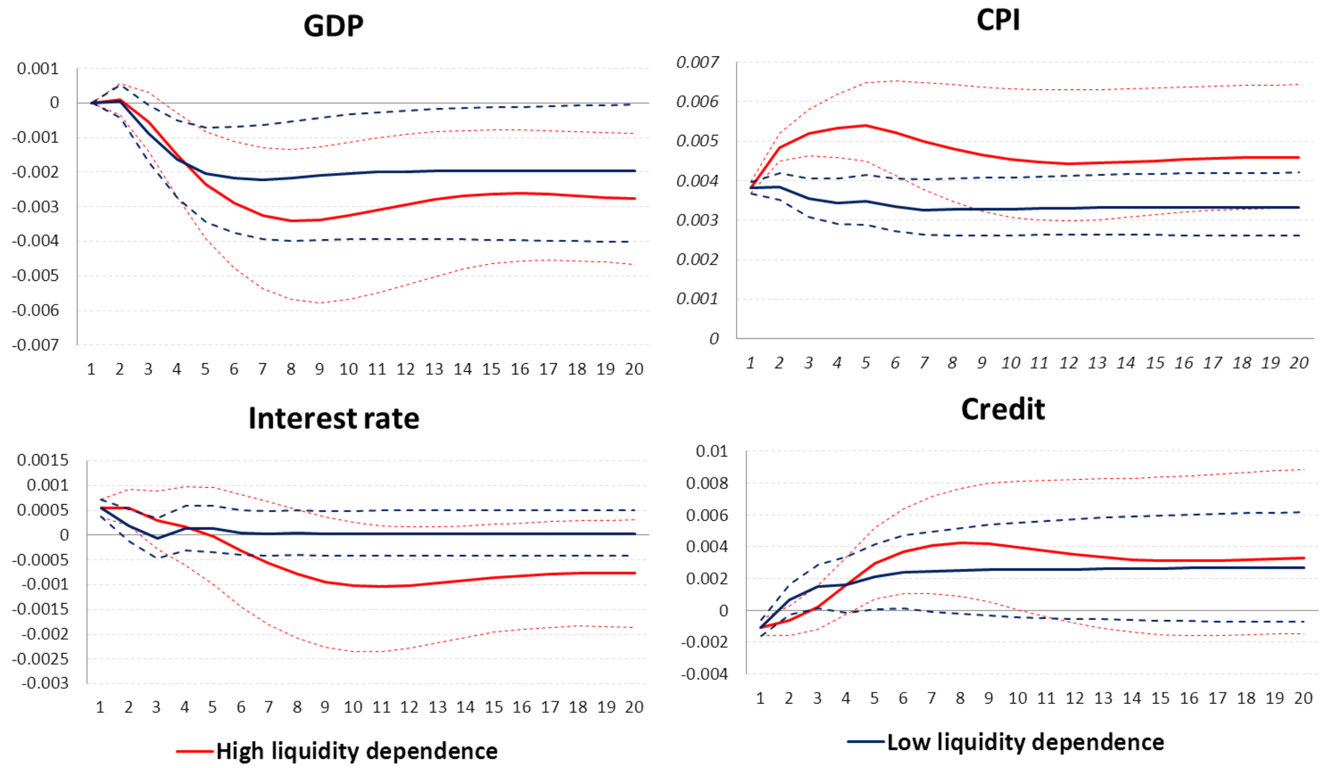


Figure 5. Impulse responses to innovation in interest rate (the median and the 16th and 84th quantiles of the distribution)

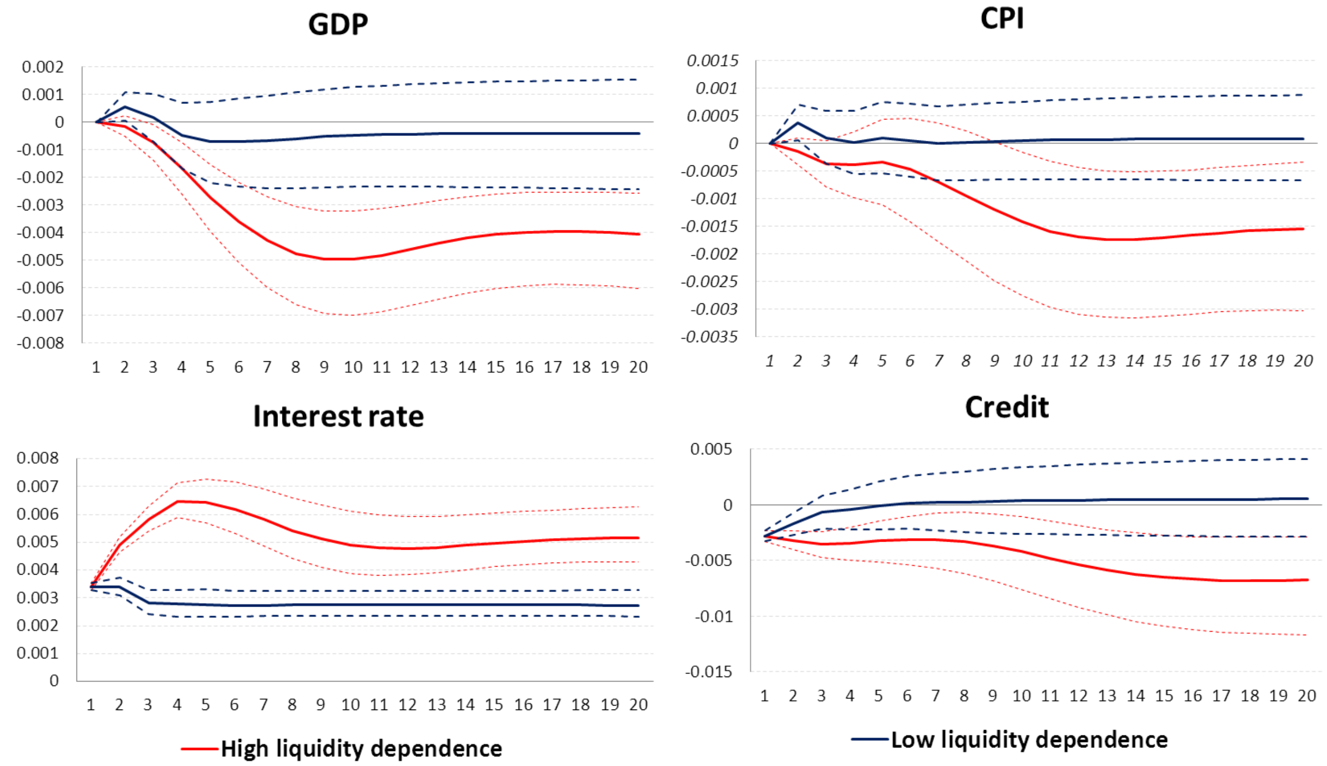
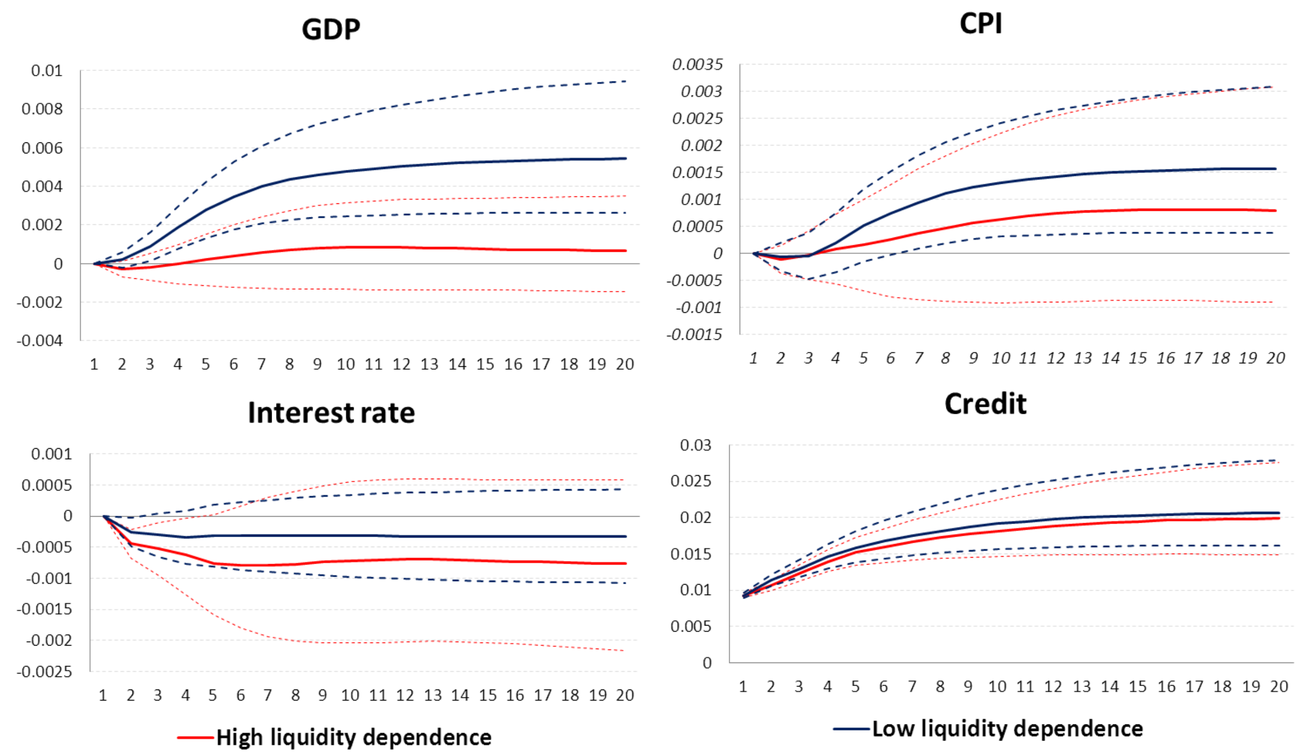


Figure 6. Impulse responses to innovation in credit (the median and the 16th and 84th quantiles of the distribution)



4.2. Predicting differences in macro-financial linkages across countries

In this section, we measure the model's ability to capture the differences in macro-financial linkages. In line with the existing literature, we concentrate on the link between financial and real variables (i.e. GDP growth). We therefore present our results in terms of the root mean squared error (RMSE) of GDP forecast at the 12 quarters horizon, calculated conditionally on actual interest rate and credit developments.

The recursive forecast in period t is calculated in the following way. We estimate mode values of hyperparameters using the time sample up to period t. We use the posterior modal covariance under these hyperparameters. Under these values, we use modal coefficients. The conditional forecast is then calculated for the period from t + 1 to t + h, where $h = \min(12, T - t)$. In the 'leave-one-out' example, we estimate parameter once for each country using data for other countries. The rest of the forecasting procedure is the same.

We compare the results with the performance of the linear panel BVAR without the smooth transition feature. This exercises also allows us to select the most relevant LD indicator as we test each of 12 sets of transition variables calculated as described in the Section 4 (although we report only the best result obtained using one of the threshold percentiles).

We use the measures of out-of-sample performance to assess the relevance of our approach to modelling the macro-financial linkages. The out-of-sample performance of time series models is usually examined by means of forecasting over different time sub-samples. In our case this approach may be impeded by the insufficient length of the series. We therefore conduct the out-of-sample experiments both in time and in cross-sectional dimensions.

Accordingly, our first approach to out-of-sample forecasting is based on a 'leave-one-out' cross validation procedure (see e.g. Murphy 2012). Namely, we estimate our model using all the countries except for country i, and then make a forecast for country i in a round-robin fashion. We then compute the RMSEs over all iterations.

The results are reported in Table 2. Three out of five LD measures allow ST-BVAR to outperform the linear BVAR. We therefore conclude that controlling for differences in liquidity dependence is useful when trying to forecast output growth conditionally on financial variables' developments.

Table 2. Forecast errors (leave-one-out approach)

LD measure (threshold percentile)	RMSE as ratio to the benchmark
CA (66)	0.94
INV (50)	0.96
STD (75)	0.98
Linear BVAR	*benchmark*
WAGE (50)	1.01
ED (75)	1.01

The second out-of-sample forecasting exercise comprises recursive estimation of the models over the expanding time sample using all countries in the cross-section and the calculation of conditional forecasts over the next 12 quarters. In addition to the linear panel BVAR, we compare the results with country-specific BVARs estimated for each country in the cross-section (admittedly the outcome of this comparison depends not only on the relevance of the smooth transition approach but also on the appropriateness of pooling data across countries).

The results are reported in Table 3. All ST-BVARs outperform the linear panel BVAR. Notably, the best performing ST-BVAR produced forecasts that were more accurate than those produced by the country-specific model. Arguably, this result indicates that pooling cross-country data in combination with using the smooth transition approach may be useful for practical forecasting (at least when dealing with relatively short time samples). We believe that this finding is noteworthy. Note that, while the instances of linear models being outperformed by non-linear versions are far from unprecedented (see e.g. Teräsvirta, van Dijk and Medeiros 2005, Alessandri and Mumtaz 2017, Nyberg 2018), the direct comparisons between the forecasting performance of panel and country-specific models are only occasionally reported in the literature (see Koop and Korabilis 2018 for a rare example).

Table 3. Forecast errors (recursive approach)

LD measure (threshold percentile)	**RMSE as ratio to the benchmark**
CA (66)	0.84
Country-specific linear BVARs	0.87
INV (50)	0.91
WAGE (50)	0.91
ED (66)	0.94
STD (75)	0.96
Linear BVAR	*benchmark*

In both types of exercises, the best performing transition variable is based on the current assets ratio measure calculated using the 66th threshold percentile. Its variation across countries is shown in Figure 5. According to this measure, Portugal appears to be the most liquidity-dependent economy, followed by Belgium and Italy, while Austria and Germany are the least dependent among advanced countries.

5. CONCLUSIONS

The concept of liquidity dependence has been frequently used in the literature to discuss the performance of various industries after the occurrence of contractionary financial shocks. Most previous studies have concluded that liquidity-dependent industries are more vulnerable to a banking crisis. Some also find that these effects may be mitigated in economies with ‘developed’ banking systems (usually represented by large banking systems).

We suggest a broader, more generalized view of the role of liquidity dependence measures. Namely, we argue that there are good theoretical reasons to believe that industries with a varying degree of reliance on external finance will react differently to shocks (whether these shocks are mitigated or amplified by the size of the banking sector is beyond the scope of this paper). Therefore, the degree of liquidity dependence is likely to be among the more important predictors of heterogeneity in macro-financial linkages across countries.

To make this argument, we estimate a panel BVAR for a cross-section of seven advanced European economies and produce out-of-sample forecasts of GDP conditionally on observed developments of interest rates and credit. We show that by using a smooth transition version of the model and allowing the parameters to vary across economies conditionally on their liquidity dependence, it is possible to improve the accuracy of the forecasts. In fact, in our exercises, the panel ST-BVAR outperformed the set country-specific BVAR models. We interpret this result as an indication of the importance of an economy’s liquidity dependence in the determination of linkages between real and financial variables.

Interestingly, we found that the liquidity-dependence measure based on the current assets ratio was more helpful in our forecasting exercise than the more widely used external dependence indicator. Note that, unlike in other studies, we have used a relatively homogenous cross-section of countries and used directly observed liquidity-dependence measures.

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ANNEX A1: A SIMPLE MODEL OF LIQUIDITY NEEDS AND AGGREGATE OUTPUT

Consider two economies, Economy L and Economy H, populated solely by the firms with low and high liquidity needs, respectively. Firms operate in two periods. At $t = 1$ each firm gets an amount of cash $\theta K_{\theta,i}$, where $K_{\theta,i}$ is a fixed amount of physical capital, and decides how much to invest in working capital ($W_{\theta,i}$) to produce at $t = 2$. Parameter θ captures the good and the bad state of the firm in terms of cash flows, which is known at $t = 1$. A good state ($\bar{\theta}$) implies a firm that is financially unconstrained, whereas the occurrence of the bad state ($\underline{\theta}$) indicates the firm is financially constrained, $\underline{\theta} < \bar{\theta} < 1$. Each economy consists of p firms of type $\bar{\theta}$ and $(1-p)$ firms of type $\underline{\theta}$, $p \in [0;1]$. Firms have the following production function: $Y_{\theta,i} = ((1-\phi)K_{\theta,i}^{\alpha} + \phi W_{\theta,i}^{\alpha})^{1/\alpha}$, where $\alpha < 1$ and $0 \leq \phi \leq 1$. Parameter ϕ shows the relative importance of working capital in the production, i.e. the measure of firm's liquidity needs. Consequently, Economy L's firms with low liquidity needs have $\underline{\phi}$, whereas firms with high liquidity needs in Economy H have $\overline{\phi}$, such that $\underline{\phi} < \overline{\phi}$.

Due to the existence of credit constraint, firms cannot invest more than a multiple of $\mu > 1$ of their cash flows,[8] i.e. $W_{\theta,i} \leq \mu\theta K_{\theta,i}$.[9] Parameter μ captures the access to financing. The market interest rate on borrowing and lending $R_{\theta,i}$ differs between two types of firms and between two economies.

Assume that both economies are at their steady state levels of output ($Y_i^*, i = L, H$), such that $Y_L^* = Y_H^*$. Firms have a fixed steady state level of physical capital, $K_{\theta,i}^*$. The aggregate level of output in each economy is defined as a weighted average of outputs produced by financially unconstrained firms ($Y_{\bar{\theta},i}$) and financially constrained firms ($Y_{\underline{\theta},i}$), i.e. $Y_i = pY_{\bar{\theta},i} + (1-p)Y_{\underline{\theta},i}$.

The optimization problem of the $\bar{\theta}$ type firm at $t = 1$ in both economies is:

$$max_{W_{\bar{\theta},i}} \left((1-\phi){K_{\bar{\theta},i}^*}^{\alpha} + \phi W_{\bar{\theta},i}^{\alpha}\right)^{\frac{1}{\alpha}} - R_{\bar{\theta},i}W_{\bar{\theta},i}$$
$$s.t. \quad W_{\bar{\theta},i} \leq \mu\bar{\theta}K_{\bar{\theta},i}^*$$

Since financial constraint is not binding for the firm in the good state, the equation for $W_{\bar{\theta},i}$ is:

$$\phi W_{\bar{\theta},i}^{\alpha-1}({K_{\bar{\theta},i}^*}^{\alpha} + \phi W_{\bar{\theta},i}^{\alpha})^{\frac{1-\alpha}{\alpha}} = R_{\bar{\theta},i}$$

By rearranging, we get the optimal amount of investment in working capital for the financially unconstrained firm (unconstrained optimum):

$$W_{\bar{\theta},i}^* = K_{\bar{\theta},i}^* \left[\left(\frac{R_{\bar{\theta},i}}{\phi}\right)^{\frac{\alpha}{1-\alpha}} - \phi\right]^{-\frac{1}{\alpha}} \tag{A.1}$$

In both economies, each firm that experiences good times in its cash flows will produce the following amount at $t = 2$:

[8] We also impose the restriction that is needed to ensure the harder impact for Economy H:

$$\left(\mu\underline{\theta}\right)^{\alpha} < 2$$

[9] Such form of the credit constraint is quite standard and can be obtained by accounting for the capital market imperfections, such as the moral hazard problem (Aghion, Bacchetta, and Banerjee 2004).

$$Y^{*}_{\overline{\theta},i} = K^{*}_{\overline{\theta},i}\left((1-\phi)+\phi\left[\left(\frac{R_{\overline{\theta},i}}{\phi}\right)^{\frac{\alpha}{1-\alpha}}-\phi\right]^{-1}\right)^{1/\alpha} \tag{A.2}$$

The optimization problem of the $\underline{\theta}$ type firm at $t = 1$ in both economies is:

$$max_{W_{\underline{\theta},i}}\left((1-\phi){K^{*}_{\underline{\theta},i}}^{\alpha}+\phi W^{\alpha}_{\underline{\theta},i}\right)^{\frac{1}{\alpha}}-R_{\underline{\theta},i}W_{\underline{\theta},i}$$
$$s.t.\quad W_{\underline{\theta},i}=\mu\underline{\theta}K^{*}_{\underline{\theta},i}$$

Each firm that experiences bad times in its cash flows faces binding financial constraint, which results in the following constraint optimum for the amount invested in working capital and the amount produced at $t = 2$:

$$W^{*}_{\underline{\theta},i}=\mu\underline{\theta}K^{*}_{\underline{\theta},i} \tag{A.3}$$

$$Y^{*}_{\underline{\theta},i}=K^{*}_{\underline{\theta},i}\left(1-\phi+\phi\left[\mu\underline{\theta}\right]^{\alpha}\right)^{1/\alpha} \tag{A.4}$$

The aggregate output produced in each economy is:

$$Y^{*}_{i}=pY^{*}_{\overline{\theta},i}+(1-p)Y^{*}_{\underline{\theta},i}=$$
$$=pK^{*}_{\overline{\theta},i}\left((1-\phi)+\phi\left[\left(\frac{R_{\overline{\theta},i}}{\phi}\right)^{\frac{\alpha}{1-\alpha}}-\phi\right]^{-1}\right)^{1/\alpha}+(1-p)K^{*}_{\underline{\theta},i}\left(1-\phi+\phi\left[\mu\underline{\theta}\right]^{\alpha}\right)^{1/\alpha} \tag{A.5}$$

ANNEX A2: EFFFECT OF FINANCIAL SHOCK ON AGGREGATE OUTPUT

We consider a change in the access to financing (μ) as an example of financial shock to examine the difference in the magnitude of the change in aggregate output in the economies with different levels of liquidity dependence. Since μ affects only the optimal working capital investment choices of financially constrained firms (equation A.3), we focus on the change in output produced by this type of firm (equation A.4), which is a part of aggregate output (equation A.5). We are going to compare the size of the change in output of financially constrained firms $(Y^*_{\underline{\theta},i})$ due to the change in μ to draw a conclusion about the amplification effect of financial shock in economies with different levels of liquidity dependence.

Since $Y^*_L = Y^*_H$ and p is the same in both economies, we consider simply the case that $Y^*_{\overline{\theta},L} = Y^*_{\overline{\theta},H}$ and $Y^*_{\underline{\theta},L} = Y^*_{\underline{\theta},H}$. Thus,

$$K^*_{\underline{\theta},L}\left(1-\underline{\phi}+\underline{\phi}[\mu\underline{\theta}]^{\alpha}\right)^{1/\alpha} = K^*_{\underline{\theta},H}\left(1-\overline{\phi}+\overline{\phi}[\mu\underline{\theta}]^{\alpha}\right)^{1/\alpha}$$

Let us set $K^*_{\underline{\theta},L} = 1$, then

$$K^*_{\underline{\theta},H} = \left(\frac{1-\underline{\phi}+\underline{\phi}[\mu\underline{\theta}]^{\alpha}}{1-\overline{\phi}+\overline{\phi}[\mu\underline{\theta}]^{\alpha}}\right)^{1/\alpha} > 0$$

The effect of change in access to financing on aggregate output is:

$$\frac{dY^*_i}{d\mu} = p\frac{dY^*_{\overline{\theta},i}}{d\mu} + (1-p)\frac{dY^*_{\underline{\theta},i}}{d\mu} = (1-p)\frac{dY^*_{\underline{\theta},i}}{d\mu}$$

The economy is said to be hit harder when access to financing changes if it has greater $\frac{dY^*_i}{d\mu}$ or, in other words, greater $\frac{dY^*_{\underline{\theta},i}}{d\mu}$.

$$\frac{dY^*_{\underline{\theta},L}}{d\mu} = \frac{\underline{\phi}(\mu\underline{\theta})^{\alpha}\left[1-\underline{\phi}+\underline{\phi}(\mu\underline{\theta})^{\alpha}\right]^{\frac{1}{\alpha}-1}}{\mu} > 0$$

$$\frac{dY^*_{\underline{\theta},H}}{d\mu} = \frac{\overline{\phi}K^*_{\underline{\theta},H}(\mu\underline{\theta})^{\alpha}\left[1-\overline{\phi}+\overline{\phi}(\mu\underline{\theta})^{\alpha}\right]^{\frac{1}{\alpha}-1}}{\mu} = \frac{\overline{\phi}(\mu\underline{\theta})^{\alpha}\left[1-\underline{\phi}+\underline{\phi}(\mu\underline{\theta})^{\alpha}\right]^{\frac{1}{\alpha}}\left[1-\overline{\phi}+\overline{\phi}(\mu\underline{\theta})^{\alpha}\right]^{-1}}{\mu} > 0$$

Since $\underline{\phi} < \overline{\phi}$,

$$\frac{\underline{\phi}}{1-\underline{\phi}+\underline{\phi}(\mu\underline{\theta})^{\alpha}} < \frac{\overline{\phi}}{1-\overline{\phi}+\overline{\phi}(\mu\underline{\theta})^{\alpha}}$$

Thus,

$$\frac{dY^*_{\underline{\theta},L}}{d\mu} < \frac{dY^*_{\underline{\theta},H}}{d\mu} \quad \text{and} \quad \frac{dY^*_L}{d\mu} < \frac{dY^*_H}{d\mu}.$$

Therefore, Economy H, which consists only of firms with high liquidity needs, is hit harder compared to low liquidity dependent Economy L when funds available for borrowing are reduced.

ANNEX B: LIQUIDITY DEPENDENCE MEASURES ACROSS ECONOMIC ACTIVITIES AND COUNTRIES

Table 4. Liquidity dependence measures across industries: median (min/max)

Economic activity	ISIC code	Liquidity-dependence measure				
		INV	CA	WAGE	STD	ED
A	Agriculture, forestry and fishing	20.8 (13.8/36)	65 (42.4/102)	64.5 (42/108)	17.7 (5/33)	0.2 (-18/0.8)
B	Mining and quarrying	9.2 (5.7/37.4)	60.4 (43.1/174)	48.5 (30.2/70.2)	14.2 (4.3/63.7)	0 (-5.9/0.8)
C10-12	Manufacture of food, beverages and tobacco products	10.9 (7.3/17.8)	35.5 (26.6/55.3)	57.9 (48.7/67.2)	10.4 (4/17.9)	-0.6 (-1/1.9)
C13-15	Manufacture of textiles, wearing apparel, leather and related products	19.2 (15.9/21.4)	50.2 (37.6/68.1)	69.1 (54.5/75.3)	12.3 (4.2/20)	-1.6 (-15.1/14)
C16	Manufacture of wood and wood products	15.1 (11.7/27.9)	42.8 (31.4/75.9)	69.1 (54.5/35.7)	15.4 (5.6/25.1)	0 (-1.4/60)
C17	Manufacture of paper and paper products	10.4 (9/14.8)	43.2 (32.6/66.6)	56 (35.7/75.2)	10 (4.6/25)	-0.6 (-4.1/4)
C18	Printing and reproduction of recorded media	7.9 (5.4/11.2)	44.5 (34.6/80.5)	69.1 (53.9/80.4)	9.9 (3.5/19.4)	0.1 (-4.4/23)
C19	Manufacture of coke and refined petroleum products	7.8 (3.1/14.5)	24.1 (14.5/62.4)	51.4 (28/246)	8 (0.7/42.9)	-0.3 (-7.5/3.5)
C20	Manufacture of chemicals and chemical products	11.6 (9.6/14.5)	47.4 (36/62.4)	58.1 (37.8/68.4)	12.6 (4.9/38)	0.1 (-4.2/23)
C21	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	17.1 (15.9/20.9)	63 (50.8/144)	49.6 (36.7/59.2)	11.4 (4.2/33)	-0.2 (-36/1)
C22	Manufacture of rubber and plastic products	11.6 (9.1/13.3)	44.1 (35.9/56.9)	64.6 (42.3/75.7)	10 (6/18.1)	-0.2 (-1.8/9.1)
C23	Manufacture of other non-metallic mineral products	14 (12/20.8)	49.2 (42.6/76.9)	62.9 (44.2/70.5)	16.2 (4.8/38.3)	-0.6 (-3.1/12)
C24	Manufacture of basic metals	15.9 (13.4/21.5)	47.7 (31.7/47)	61.2 (55.4/75.7)	11.2 (4.8/20.9)	0.2 (-1.3/63)
C25	Manufacture of fabricated metal products	16 (11.5/19.2)	52.3 (39.5/70)	71 (58.8/77.5)	8.9 (3.7/17.6)	-0.1 (-2/2.5)
C26	Manufacture of computer, electronic and optical products	14.4 (7.5/19.4)	60.6 (26.3/83.8)	69.2 (56.9/90.7)	7.8 (3.2/38.4)	0 (-4.8/1.4)
C27	Manufacture of	14	57.6	66.6	7.9	-0.2

	electrical equipment	(10.9/21.2)	(36.7/63.9)	(53.5/80.3)	(3.3/18)	(-43/0.9)
C28	Manufacture of machinery and equipment n.e.c.	18.2 (16.1/24.2)	59.9 (44.5/73)	68.5 (59.3/76.2)	9.2 (3.3/16.8)	-0.1 (-1.6/14)
C29	Manufacture of motor vehicles, trailers and semi-trailers	6 (5.2/10.2)	31.7 (27.3/44.9)	65.3 (44.5/81.5)	5.2 (3.1/20.5)	-0.5 (-2.1/17)
C30	Manufacture of other transport equipment	17.1 (21.3/67.2)	86.6 (58.8/157)	72.9 (56.1/94.9)	15 (2.6/25.8)	0.2 (-5.6/3.8)
C31-32	Other manufacturing	10.4 (11.9/35.9)	51.6 (33.7/72.2)	70.3 (63/79.4)	8.7 (4.8/21.8)	-0.3 (-13/3.6)
C33	Repair and installation of machinery and equipment	14.9 (8.7/35.9)	59.2 (33.7/73.6)	79.5 (63/85)	5.8 (3.7/16.5)	0.3 (-0.6/1)
D	Electricity, gas, steam and air conditioning supply	2.9 (1.7/14.2)	49.5 (34.6/104)	34.9 (17/67.6)	11.8 (3.1/41)	-0.5 (-23/16)
E	Water supply; sewerage, waste management and remediation activities	3.6 (3/14.8)	70.7 (32.4/146)	55.2 (16.3/69.5)	17.9 (3.9/36.7)	0.4 (-57/1.5)
F	Construction	23.8 (6.8/67.1)	71.3 (38.9/144)	68 (45.8/83.6)	12.3 (5.1/38.1)	0.5 (-0.9/3.3)
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	9.9 (7.9/12.9)	33.7 (25.5/52.6)	64.9 (55.2/72.9)	6 (4.2/13)	-0.7 (-4.5/0.3)
H	Transportation and storage	2.6 (1.3/3.7)	50.3 (22.9/97)	71.6 (54.3/79.1)	11.5 (2.9/55.8)	0 (-29/1.6)
I	Accommodation and food service activities	3.3 (1.7/10.4)	39 (28/63.9)	74.8 (61.1/89.4)	15.8 (3.7/28.1)	0.7 (0.2/1)
J	Information and communication	3.3 (2.7/3.9)	54.2 (25.8/66.3)	52.7 (40.5/65.4)	12.4 (4.4/46.8)	-0.3 (-43/2.3)
L	Real estate activities	21.5 (3.9/230.3)	135.4 (41.9/355)	31.4 (23.9/59.1)	68.5 (4.2/142)	0.4 (-2/4)
M	Professional, scientific and technical activities	6.8 (4.5/14)	120.1 (55.7/998)	68.5 (15.5/83.4)	27.4 (7.8/482)	-0.5 (-29/1.7)
N	Administrative and support service activities	2.4 (1.4/6.6)	56.5 (34.7/76.2)	71.9 (58.3/82.1)	19.3 (7.7/31.8)	-0.3 (-131/0.8)
P	Education	1.8 (1.1/3.8)	48.7 (27.5/56.9)	83.1 (43.6/88.5)	6.9 (3.4/18.7)	0.1 (-2.7/5.3)
Q	Human health and social work activities	10.4 (9/14.8)	40.5 (24.1/69.6)	77.5 (47.3/89.1)	7.3 (3.4/18.3)	0.1 (-0.7/144)
R	Arts, entertainment and recreation	2.2 (0.5/4.2)	47.6 (20.7/84.4)	63.7 (41.8/106)	10.1 (4/49.8)	0.2 (-6.7/1.5)
S	Other service activities	10.4 (9/14.8)	44.6 (14/80.1)	74.1 (9/87.6)	9.2 (2.9/23.9)	0.4 (-3/1)

Table 5. Countries and industries with average current assets ratio above 66th threshold

Industry \ Country	PT	IT	BE	ES	FR	DE	AT	CZ	SK	PL	Number of countries with industry's CA above 66th threshold (out of 10)
L	*	*	*	*	*	*	*	*	*	*	10
C30	*	*	*	*	*	*	*	*		*	9
F	*	*	*	*	*	*	*			*	8
M	*		*	*	*	*	*	*	*		8
A	*	*		*	*			*	*	*	7
C21	*	*	*	*		*		*	*		7
C28	*	*	*	*	*		*				6
B	*		*	*	*	*					5
C26		*	*		*	*	*				5
C33	*	*		*	*	*					5
E	*	*	*	*					*		5
C23	*	*	*	*							4
C27	*	*	*				*				4
H	*	*		*	*						4
J	*	*	*	*							4
R	*	*	*					*			4
C31-32	*	*		*							3
N			*						*	*	3
C13-15	*	*									2
C16	*	*									2
C18	*	*									2
C25	*	*									2
D	*				*						2
Q	*		*								2
S	*	*									2
C17	*										1
C20			*								1
I	*										1
C10-12											0
C19											0
C22											0
C24											0
C29											0
G											0
P											0
Number of industries within a country with CA above 66th threshold (out of 35)	25	20	16	14	11	8	7	6	6	5	118

Table 6. Average values of transition variables based on alternative LD measures

LD measure:	INV			CA			WAGE			STD			ED			
Threshold percentile:	25	33	50	25	33	50	25	33	50	25	33	50	25	33	50	
Austria	0.75	0.72	0.47	0.35	0.30	0.14	0.48	0.85	0.99	0.27	0.32	0.39	0.72	0.79	0.95	Austria
Belgium	0.68	0.64	0.35	0.68	0.72	0.89	0.08	0.06	0.29	0.51	0.54	0.77	0.02	0.02	0.24	Belgium
Czech Republic	0.28	0.22	0.05	0.04	0.03	0.08	0.07	0.03	0.02	0.21	0.19	0.21	0.25	0.58	0.43	Czech Republic
France	0.14	0.18	0.16	0.55	0.51	0.72	0.98	0.99	0.89	0.33	0.28	0.23	0.34	0.47	0.64	France
Germany	0.81	0.79	0.64	0.43	0.29	0.19	0.74	0.62	0.68	0.79	0.94	0.99	0.57	0.50	0.86	Germany
Italy	0.58	0.59	0.95	0.89	0.67	0.59	0.01	0.15	0.52	0.91	0.94	0.93	0.28	0.25	0.07	Italy
Poland	0.01	0.02	0.19	0.05	0.13	0.02	0.12	0.14	0.02	0.01	0.01	0.01	0.21	0.15	0.04	Poland
Portugal	0.95	0.89	0.92	0.96	0.98	0.99	0.28	0.17	0.30	0.98	0.98	0.87	0.47	0.32	0.67	Portugal
Slovak Republic	0.25	0.15	0.21	0.20	0.15	0.25	0.07	0.05	0.31	0.13	0.17	0.20	0.51	0.51	0.81	Slovak Republic
Spain	0.83	0.93	0.90	0.45	0.56	0.48	0.57	0.62	0.86	0.60	0.77	0.76	0.96	0.97	0.94	Spain

Colours by range	0–20	21–40	41–60	61–80	81–100

ANNEX C: IMPULSE RESPONSES OBTAINED USING THE DATASET INCLUDING BOTH ADVANCED AND EMERGING MARKET ECONOMIES

Figure 7. Impulse responses to innovation in GDP (median and the 16th and 84th quantiles of the distribution)

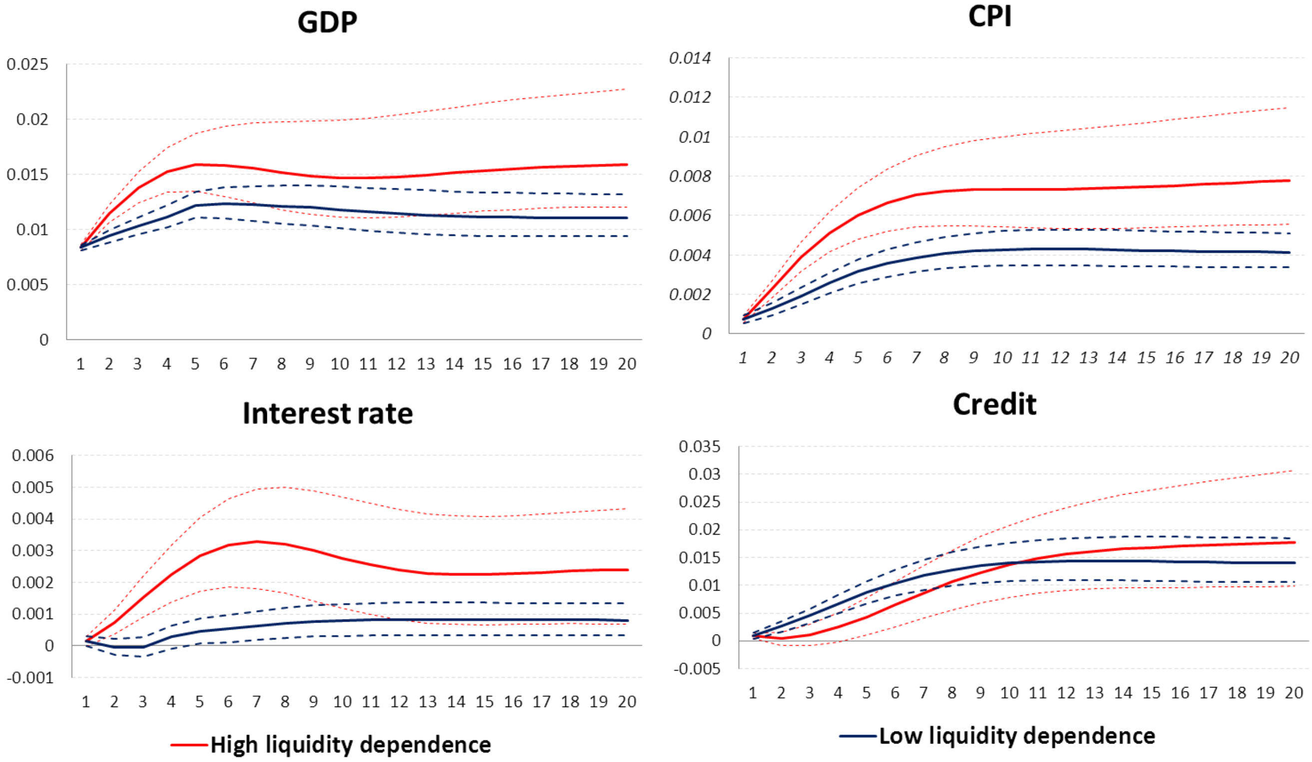

Figure 8. Impulse responses to innovation in CPI (median and the 16th and 84th quantiles of the distribution)

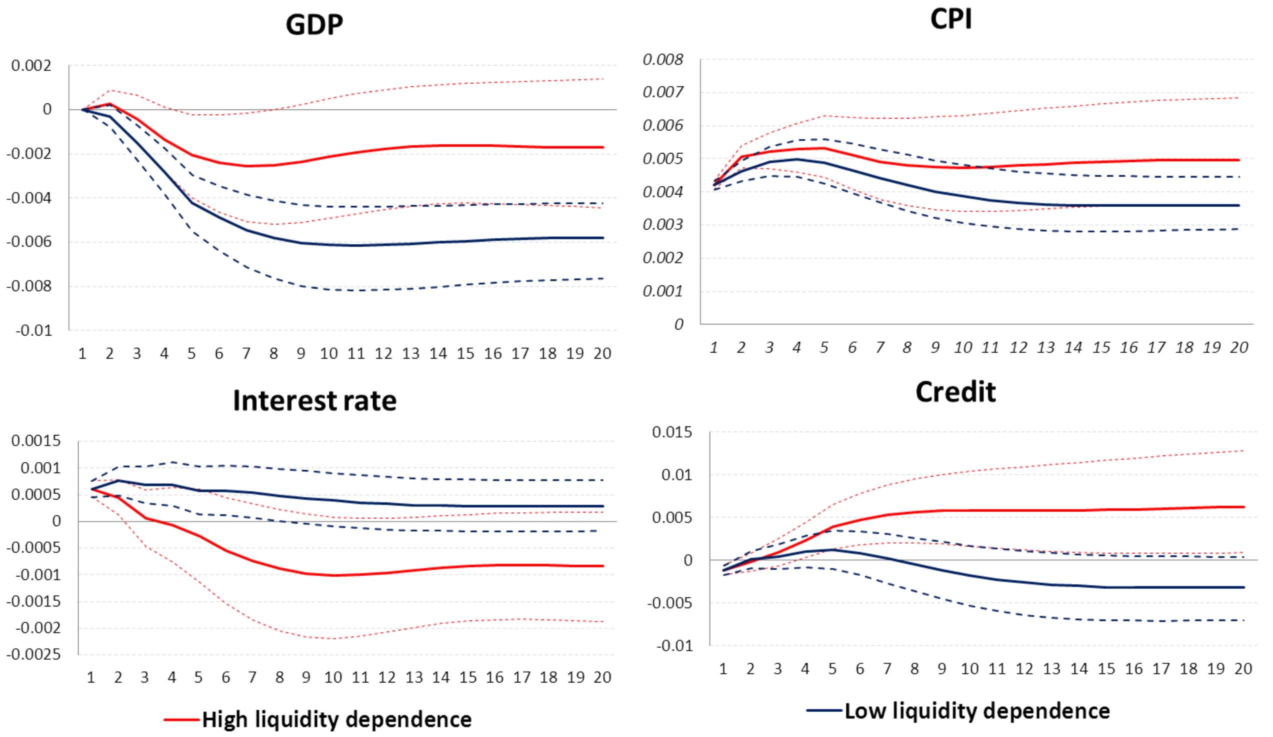

Figure 9. Impulse responses to innovation in interest rate (median and the 16th and 84th quantiles of the distribution)

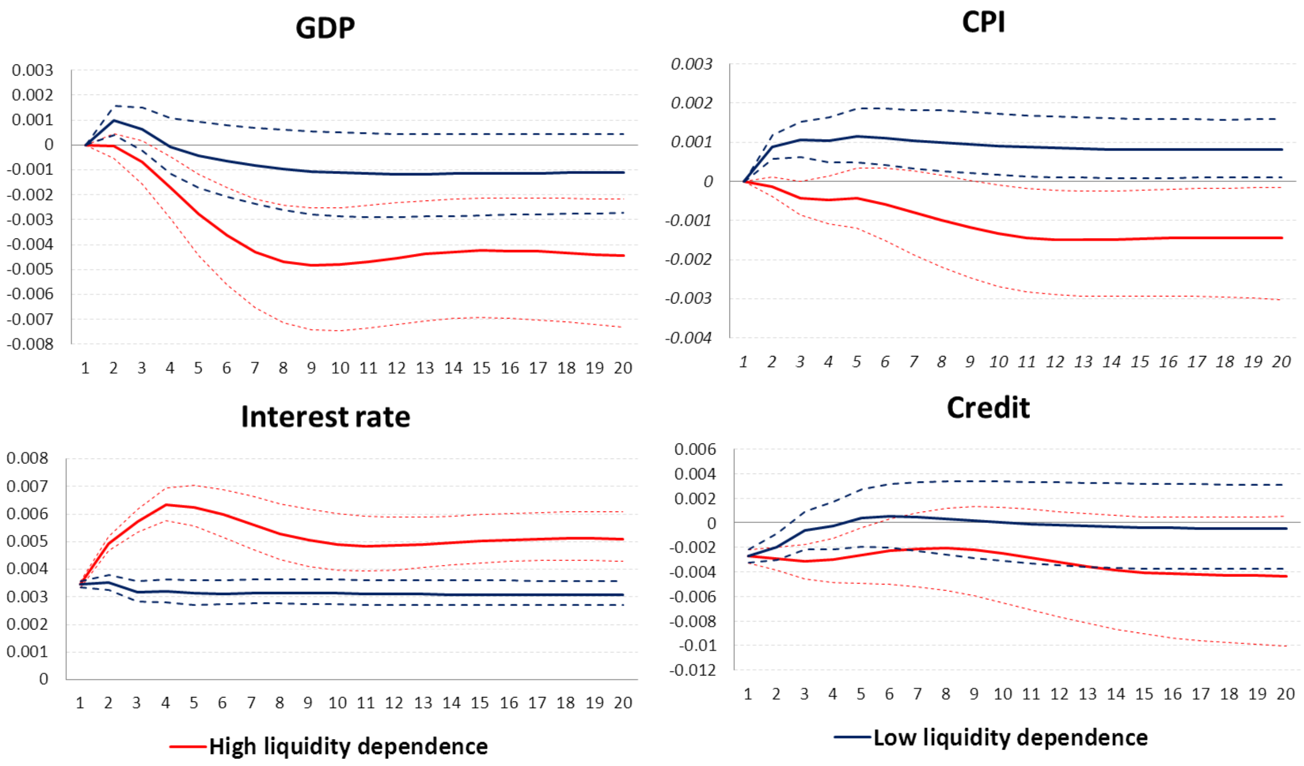

Figure 10. Impulse responses to innovation in credit (median and the 16th and 84th quantiles of the distribution)