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Uncertainty and Demand for Business Loans: A Study of Selected Countries in the Euro Area

Summary: This paper studies the effect of uncertainty shocks on the demand for business loans in individual euro area countries. The results of Bayesian vector autoregression (VAR) model impulse response functions show that in some countries the overall demand for business loans, and particularly the demand for business loans for fixed-investment financing, respond significantly negatively to the shock.

Keywords: Demand for business loans, Uncertainty, Bayesian VAR.

JEL: D81, E32, E44.

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It was not until recently that research has shown that uncertainty shocks affect the supply and demand for loans (e.g. Nathan S. Balke and Zheng Zeng 2013; Simon Gilchrist, Jae W. Sim, and Egon Zakrajsek 2014; Claudia M. Buch, Manuel Buchholz, and Lena Tonzer 2015; Piergiorgio Alessandri and Margherita Bottero 2017; Ekaterina Pirozhkova 2017; Fabián Valencia 2017), however, empirical studies investigating the effects of uncertainty shocks on demand for loans are rare. In this respect, Balke and Zeng (2013) investigated the effect of uncertainty shocks on the demand for loans focusing on the United States. The aim of this paper is to complement existing literature by assessing the impact of uncertainty shocks on the overall demand for business loans and the demand for business loans for fixed-investment financing in individual euro area countries.

An important challenge in this task is to identify (or measure) the demand for loans. To do this, Balke and Zeng (2013) employ a factor model with various credit market indicators and sign restrictions. There are also other approaches in the literature to identify demand for loans: Marting M. G. Fase (1995) assumes that dynamics of loans is primarily determined by demand for loans, while Kazuo Ogawa and Kazuyuki Suzuki (2000) observe loan demand of individual firms.

This paper applies data from the European Central Bank Euro Area Bank Lending Survey (hereinafter: EABLS), following a part of literature related to monetary policy transmission (e.g. Cara Lown and Donald P. Morgan 2006; Mattero Ciccarelli, Angela Maddaloni, and Jose Luis Peydró 2015; Silvo Dajčman 2016, 2017) to identify the overall demand for business loans and the demand for business loans for fixed-investment financing. In addition, the Country-Level Index of Financial Stress (CLIFS) data, constructed by Thibaut Duprey, Benjamin Klaus, and Tuomas Peltonen (2017) and provided by the European Central Bank (ECB 2018a)[1], is applied as an indicator of uncertainty in the countries investigated. The relationship between the uncertainty shocks and the response of demand for business loans is studied by the Bayesian

[1] **European Central Bank.** 2018a. Country-Level Index of Financial Stress. https://sdw.ecb.europa.eu/browse.do?node=9693347 (accessed April 02, 2018).

VAR and the impulse response analysis. The results show that in some parts of the euro area, uncertainty shocks do affect the overall demand for business loans and the demand for business loans for fixed-investment financing.

1. Literature Review

Existing literature has extensively examined the role of uncertainty shocks for different (macro-)economic variables (e.g. Nicholas Bloom 2009, 2014; Bloom et al. 2012; Rüdiger Bachmann and Christian Bayer 2013; Valentina Colombo 2013; Benjamin Born and Johannes Pfeifer 2014; Scott R. Baker, Bloom, and Steven J. Davis 2016; Susanto Basu and Brent Bundick 2017; Phillip Meinen and Oke Roehe 2017; Angus Moore 2017). Only recently has theoretical and empirical work stressed the role of a (non-frictionless) financial market as an amplifier of uncertainty shocks working through to economic activity (Cristina Arellano, Yan Bai, and Patrick J. Kehoe 2012, 2016; Balke and Zeng 2013; Lawrence J. Christiano, Roberto Motto, and Massimo Rostagno 2014; Gilchrist, Sim, and Zakrajsek 2014; Dario Bonciani and Björn van Roye 2015; Pirozhkova 2017). While a strand of literature has focused on the supply side of financial intermediation, showing that uncertainty shocks lead risk-averse banks to reduce loan supply (Balke and Zeng 2013; Gilchrist, Sim, and Zakrajsek 2014; Buch, Buchholz, and Tonzer 2015; Alessandri and Bottero 2017; Pirozhkova 2017; Valencia 2017), it must be noted that uncertainty shocks also affect the demand side of the loan market (Balke and Zeng 2013; Arellano, Bai, and Kehoe 2016; Pirozhkova 2017; Valencia 2017).

Existing literature lists some explanations or channels through which uncertainty shocks may exert a negative effect on the demand for loans. The first explanation rests on the assumption of imperfect credit markets in which uncertainty strengthens the information problems in the credit market and increases business cycle fluctuations (Balke and Zeng 2013; Christiano, Motto, and Rostagno 2014; Gilchrist, Sim, and Zakrajsek 2014; Arellano, Bai, and Kehoe 2016; Pirozhkova 2017; Valencia 2017). Pirozhkova (2017) notes that uncertainty not only negatively affects the supply but also the demand for loans because the external finance premium increases with uncertainty. Similarly, Arellano, Bai, and Kehoe (2016) argue that due to increased volatility (uncertainty), enterprises become more cautious and borrow less.

Next, the real options channel explains that investment activity in aggregate is expected to respond negatively to an uncertainty shock since it may be more profitable for enterprises to wait how the future and uncertainty pan out, therefore they invest less (Bloom 2009, 2014). The demand for loans is likely to change in the same direction (Valencia 2017).

The precautionary saving channel suggests that (precautionary) savings are likely to increase in times of uncertainty (e.g. Hayne E. Leland 1968; Agnar Sandmo 1970; Miles S. Kimball 1990; Bloom 2014). In such cases, not only is consumption adversely affected, but also investment activity (Jesús Fernandez-Villaverde et al. 2011; Bloom 2014; Basu and Bundick 2017). Again, the demand for loans is likely to share the dynamics of investment activity.

A similar prediction for the demand for business loans upon a shock in uncertainty can also be observed in literature that investigates the optimal financial leverage of enterprises and shows that uncertainty reduces the optimal level of financial leverage (e.g. Christopher F. Baum, Andreas Stephan, and Oleksandr Talavera 2009; Baum, Atreya Chakraborty, and Boyan Liu 2010).

Contrary to the above explanations, Bloom (2014) argues that the Oi-Hartman-Abel effect (Walter Y. Oi 1961; Richard Hartman 1972; Andrew B. Abel 1983) explains that, in an era of increased uncertainty, individual enterprises may be prompted to invest more when the potential loss of an unsuccessful project is relatively small compared to the potential profit. As previously mentioned, this may impact (stimulate) the demand for loans.

Given the opposing conclusions from the theory on the role that uncertainty plays in the demand for business loans, it is a matter of empirical research to determine whether an increase in uncertainty is detrimental or stimulating to the demand for business loans.

Empirical studies on the effects of uncertainty shocks on the (macro-)economy predominantly apply the VAR modelling approach and mostly find that uncertainty shocks are detrimental to (macro-)economic variables (see e.g. Bloom 2009; Bloom et al. 2012; Bachmann and Bayer 2013; Colombo 2013; Born and Pfeifer 2014; Baker, Bloom, and Davis 2016; Basu and Bundick 2017; Meinen and Roehe 2017; Moore 2017); (see Bloom 2014 and Born and Pfeifer 2014 for a review of studies). Balke and Zeng (2013) produced the only study on the effect of uncertainty shocks on the demand for loans for the United States in the period from January 1985 to December 2011. For this purpose, they estimated a common factor model on a large set of economic variables and imposed restrictions of regression coefficients to identify credit demand, supply, and financial intermediation factors. Once they had identified the credit market factors, they employed a Bayesian VAR modelling approach to assess the responses of endogenous variables to orthogonal shocks. The results of their study show that uncertainty shocks lead to a short-run contraction in output, financial intermediation, and the demand for loans.

2. Methodology

The relationship between uncertainty and the demand for business loans is investigated by the VAR model, which in general can be expressed as (e.g. Gary Koop and Dimitris Korobilis 2009; Helmut Luetkepohl 2011; Bonciani and van Roye 2015):

$$x_t = a + C_1 x_{t-1} + C_2 x_{t-2} + \cdots + C_p x_{t-p} + \varepsilon_t, \quad (1)$$

where x_t is an $Nx1$ vector of endogenous variables, the selection of which is guided by recent studies on the effects of uncertainty on the (macro-)economy (e.g. Bloom 2009; Colombo 2013; Bonciani and van Roye 2015; Baker, Bloom, and Davis 2016; Basu and Bundick 2017; Moore 2017; Pirozhkova 2017), literature on demand for business loans (Fase 1995; Ogawa and Suzuki 2000; Christoffer Kok Sørensen, David Marqués Ibáñez, and Carlotta Rossi 2012) and literature that uses the results of bank lending surveys (e.g. Lown and Morgan 2006; Ciccarelli, Maddaloni, and Peydró 2015; Dajčman 2016, 2017). The endogenous variables included are: the Country-Level Index of Financial Stress ($CLIFS$) as an indicator for uncertainty, a logarithm of harmonized index of consumer prices ($lnHICP$), the average interest rate on business loans (ir), a logarithm of real gross domestic product ($lnrGDP$), and the EABLS indicator of overall demand for business loans (dl). C_i ($i = 1, \dots, p$) in the model above is a NxN matrix of regression coefficients, t is time ($t = 1, \dots, T$) (in our case in quarters), p is the number of lags of the endogenous variables (determined by DIC as explained below), a is a $Nx1$ vector of a constant, while a vector of residuals ($Nx1$) of the model is represented by ε_t. The vector of endogenous variables is thus:

$$x_t = [CLIFS\ lnHICP\ ir\ lnrGDP\ dl]'. \quad (1a)$$

Models with up to four lags were considered and then the optimal lag was determined by the deviance information criterion (DIC) (see David J. Spiegelhalter et al. 2002; Alistair Dieppe, Romain Legrand, and van Roye 2018). In the continuation, the model (1) with this set of endogenous variables will be referred to as model (1a).

In terms of the variable $CLIFS$, note that uncertainty is not unanimously defined (Bloom 2014), and several indicators have been constructed in empirical literature (for a review, see e.g. Amélie Charles, Olivier Darné, and Fabien Tripier 2017) to measure it. In this paper, the uncertainty is proxied by the CLIFS, constructed by Duprey, Klaus, and Peltonen (2017) and provided by the ECB (2018a), which is conceptually a financial stress index compiled for all European

Union countries as a composite of stock, sovereign bond, and exchange rate market volatility (Duprey, Klaus, and Peltonen 2017), for the following reasons: (i) commonly, uncertainty is defined in terms of financial (markets) uncertainty (Bloom 2014; Laurent Ferrara, Stéphane Lhuissier, and Tripier 2017), which CLIFS also reflects (see and Dániel Holló, Manfred Kremer, and Marco Lo Duca 2012 and Duprey, Klaus, and Pelton 2017) on how financial stress reflects uncertainty; (ii) it is readily available in the ECB database (ECB 2018a) for all countries in this sample; and (iii) a financial market indicator of uncertainty and other indicators of uncertainty are mostly highly correlated (Bloom 2014; Ferrara, Lhuissier, and Tripier 2017).

The overall demand for business loans (dl) is taken from the EABLS, which traces the evolution of the demand for business loans in the euro area (see Petra Köhler-Ulbrich, Hannah S. Hempell, and Silvia Scopel 2016; ECB 2018b[2]).

As discussed in the Literature review section, demand for business loans may be susceptible to uncertainty shocks due to the effect of uncertainty on business investment decisions, therefore, as an alternative to model (1a), dl is substituted by the indicator of demand for business loans for fixed-investment financing – dl_fi – which is assumed as being represented by the EABLS answer to the question 'impact of fixed investment' factor for (overall) business loan demand (see Köhler-Ulbrich, Hempell, and Scopel 2016; ECB 2018b or any issue of EABLS for details of the survey, and e.g. Ciccarelli, Maddaloni, and Peydró 2015; Dajčman 2016, 2017 making assumptions based on the bank lending survey results in researching monetary policy). More detail about variables dl and dl_fi is shown in Table 1. The vector of endogenous variables (1a) thus changes to:

$$x_t = [CLIFS\ lnHICP\ ir\ lnrGDP\ dl\_fi]'. \tag{1b}$$

Model (1) with this set of endogenous variables will be referred to as model (1b).

The variables entering models (1a) and (1b) are in log levels, except uncertainty, interest rates, and the demand for loans, which is common in existing literature (see Bloom 2009; Colombo 2013; Baker, Bloom, and Davis 2016; Basu and Bundick 2017; Meinen and Roehe 2017; Moore 2017).

Following the listed literature, Choleski identification of shocks is applied, thus making the order of variables in the VAR model (1a and 1b, respectively) relevant. Akin to Bloom (2009), Baker, Bloom, and Davis (2016), Meinen and Roehe (2017) and Basu and Bundick (2017), the uncertainty indicator ($CLIFS$) is placed first, followed by price indicators ($lnHICP$ and ir), quantities of output ($lnGDP$) and demand for business loans (dl and dl_fi respectively). The credit market variable (i.e. demand for business loans) is placed after the price and output indicators, as in e.g. Balke and Zeng (2013) or Dajčman (2017). This ordering of variables assumes that $CLIFS$ contemporaneously affects $lnHICP$, ir, $lnGDP$, and dl (dl_fi respectively).

Both versions of model (1) are estimated by Bayesian methods based on quarterly data spanning the period Q1 2003 to Q4 2017 (see data description for details). An advantage of Bayesian estimation, as noted by Christopher A. Sims, James H. Stock, and Mark W. Watson (1990), is that the inference based on Bayesian estimation need not account for non-stationarity (on advantages of Bayesian methods see also e.g. Fabio Canova 2007; Koop and Korobilis 2009; Silvia Miranda-Agrippino and Giovanni Ricco 2018).

Let us rewrite model (1) in a form convenient for the Bayesian estimation (Canova 2007; Koop and Korobilis 2009; Dieppe, Legrand, and van Roye 2016, 2018):

$$x = (I_N \otimes Y)\beta + \varepsilon, \tag{2}$$

[2] **European Central Bank.** 2018b. Bank Lending Survey. https://sdw.ecb.europa.eu/browse.do?node=9691151 (accessed April 12, 2018).

where x is an $NT \times 1$ vector of the variables obtained by stacking sequentially (T) observations of the N variables, ε is a corresponding vector of residuals distributed as $N(0, \Sigma \otimes I_N)$, $Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix}$ is a $T \times M$ matrix ($M = 1 + Np$), where $y_t = \left(1, x'_{t-1}, \dots, x'_{t-p}\right)$, and $\beta = vec(B)$ is an $MN \times 1$ vector of regression coefficients, where $B = (a\, C_1\, C_2 \dots C_p)'$ (Koop and Korobilis 2009).

To estimate model (2), a normal-Wishart prior distribution is assumed (Sune Karlsson 2012; Dieppe, Legrand, and van Roye 2016, 2018; Meinen and Roehe 2017):

$$\beta \sim N(\beta_0, \Sigma \otimes Z_0), \tag{3}$$

where β_0 is the (Minnesota) prior value assumed for the regression coefficients, Σ is the variance-covariance matrix of residuals of the ordinary VAR, Z_0 is a diagonal variance matrix with elements $\sigma_{ij}^2 = (\frac{1}{\sigma_j^2})(\frac{\lambda_1}{l^{\lambda_3}})^2$ for the lag terms (where i and j denote variables in the model, l denotes lag, σ_j^2 is the variance of residuals for variable j in the Bayesian VAR model (2), estimated by the autoregression model) and for the constant the variance is $\sigma_c^2 = (\lambda_1 \lambda_4)^2$ (Karlsson 2012; Dieppe, Legrand, and van Roye 2016, 2018; Meinen and Roehe 2017).

Bearing in mind that some variables entering models (1a) and (1b), (2) respectively, may be stationary in levels while some unit root, the empirical praxis is followed (e.g. Mattias Villani 2009; Pär Österholm 2010; Dieppe, Legrand, and van Roye 2016, 2018) by setting $\beta_0 = 0.9$ for the own first lags regression (autoregressive) coefficients. For hyperparameters, the values that are commonly applied in existing literature are used (Österholm 2010; Meinen and Roehe 2017; Dieppe, Legrand, and van Roye 2016, 2018; see also Villani 2009): $\lambda_1 = 0.2$, $\lambda_3 = 1$, and $\lambda_4 = 100$.

Prior distribution for Σ is inverse-Wishart (Karlsson 2012; Dieppe, Legrand, and van Roye 2016, 2018):

$$\Sigma \sim IW(S_0, \alpha_0), \tag{4}$$

where S_0 is the diagonal matrix for the prior, with elements equal to the diagonal elements of the variance-covariance matrix obtained from individual AR regressions and multiplied by $\alpha_0 - N - 1$, and α_0 denotes the prior degrees of freedom set to $\alpha_0 = N + 2$ (Dieppe, Legrand, and van Roye 2016, 2018).

For derivation of posteriors see Koop and Korobilis (2009), Karlsson (2012) or Dieppe, Legrand, and van Roye (2016, 2018). The posterior used in this paper is of the same type as prior and as specified in Dieppe, Legrand, and van Roye (2018) and applied in their BEAR software codes. The results are presented (in Figures 2 and 3 in continuation) in the form of orthogonal impulse responses to one standard deviation shocks and are drawn with 95% confidence intervals. Gibbs sampling with 15,000 iterations and 10,000 burn-in iterations (see Dieppe, Legrand, and van Roye 2018) is used to generate the impulse responses and confidence intervals. For computations, the BEAR software codes of Dieppe, Legrand, and van Roye (2018) are used.

3. Data and Empirical Results

The empirical models described in the previous section are estimated for a set of euro area countries including Austria, Belgium, France, Greece, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. The period covered is Q1 2003 to Q4 2017, except Austria where the data covers the period from Q1 2003 to Q3 2017. The data is described in Table 1.

Table 1 Data Description

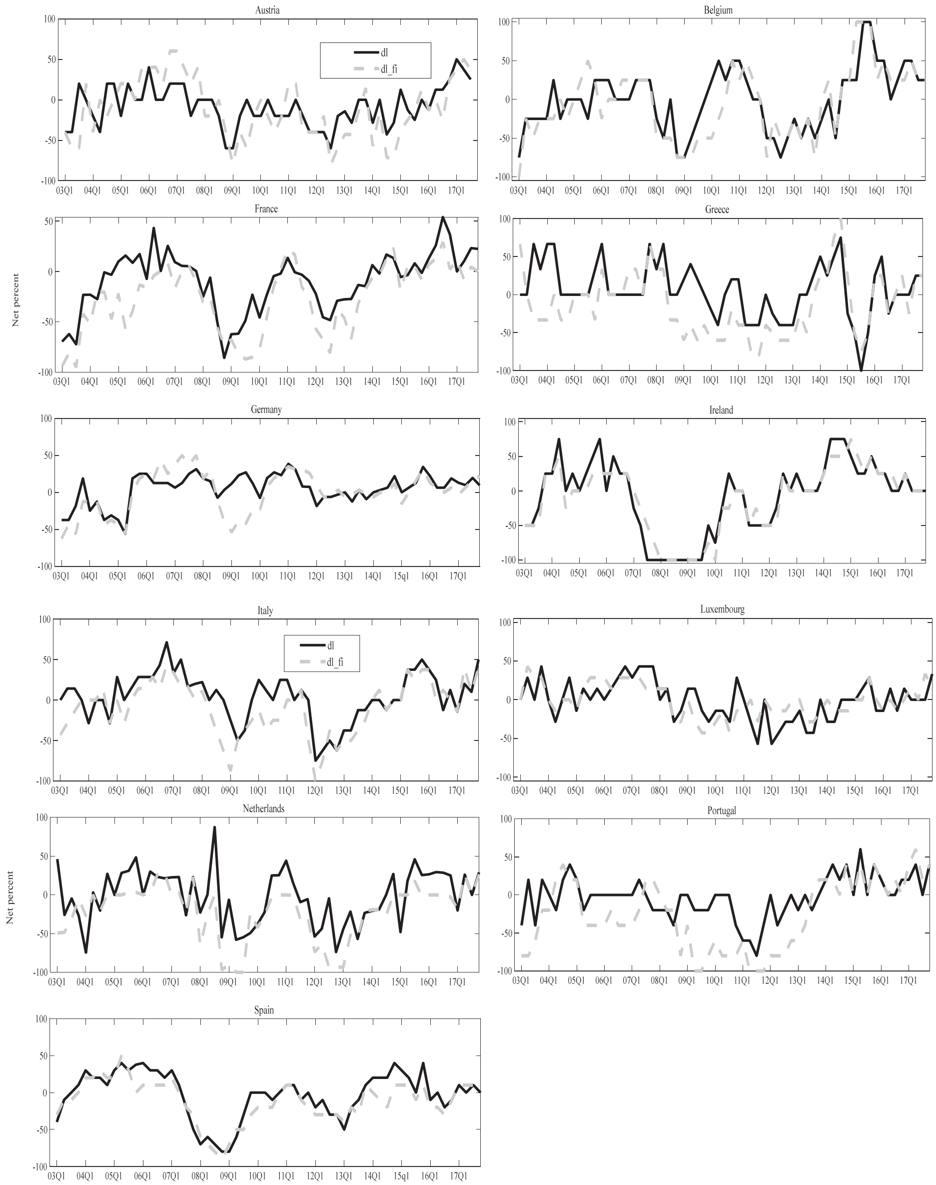
Notation of variable	Definition	Source
$CLIFS$	Country-level index of financial stress, average quarterly level calculated from monthly data (index is constructed by Duprey, Klaus, and Peltonen 2017) and provided by the ECB. $CLIFS$ is used as an indicator of uncertainty.	ECB Statistical Data Warehouse (ECB 2018a)
$lnHICP$	Natural logarithm of harmonized index of consumer prices, end of quarter value.	Eurostat (2018a)[3]
ir	Average interest rate on business (to non-financial corporations, sum of A2A and A2Z balance sheet items, see ECB 2018c) loans; quarterly average calculated from monthly data.	ECB Statistical Data Warehouse (ECB 2018c[4])
$lnrGDP$	Natural logarithm of the index of real gross domestic product, chain-linked volume, seasonally and calendar adjusted. Quarterly data.	Eurostat (2018b)[5]
dl	The overall demand for business loans. The variable is from EABLS, measured in net percent as the difference between the sum of percentages of the EABLS respondents stating a "considerable" and "somewhat" increase and the sum of percentages of survey respondents stating a "considerable" and "somewhat" decrease in the overall demand for business loans (loans to enterprises) (see Köhler-Ulbrich, Hempell, and Scopel 2016; ECB 2018b, and any issue of the EABLS on the ECB website - ECB 2018d[6]). Quarterly data.	ECB Statistical Data Warehouse (ECB 2018b)
dl_fi	The demand for business loans for fixed-investment financing. The variable is from EABLS, measured in net percent as the difference between the percentage of the EABLS respondents stating that the "impact of fixed investment" factor contributed to an increase and the percentage of respondents stating that the factor contributed to a decrease in demand for business loans (see Köhler-Ulbrich, Hempell, and Scopel 2016; ECB 2018b; and any issue of the EABLS on the ECB website -ECB 2018d). Quarterly data.	ECB Statistical Data Warehouse (ECB 2018b)

Source: Author's compilation.

Figure 1 depicts the evolution of the overall demand for business loans (dl) and the demand for business loans for fixed-investment financing (dl_fi), based on ECB (2018b) data.

The figure conveys several periods of different length with negative values of dl and dl_fi. The demand, as observed by the banks in the EABLS, fell considerably across the euro area during 2008-2009, with some difference between the investigated countries – the fall was very pronounced in Ireland and Spain, while it was less so in Germany. A rebound in demand for loans can be observed in most of the countries during 2010. In several of the countries observed, a reduced demand is noted again at the end of 2011 and the start of 2012. An important finding is that during the periods of demand reduction the dl_fi curve is normally positioned below the dl curve, indicating that banks observed a greater decline in the (factor of) demand for loans for fixed-investment financing than in the overall demand for business loans.

[3] **Eurostat.** 2018a. HICP Monthly Data. https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_midx&lang=en (accessed April 06, 2018).
[4] **European Central Bank.** 2018c. Interest Rates. https://sdw.ecb.europa.eu/browse.do?node=9691382 (accessed April 18, 2018).
[5] **Eurostat.** 2018b. GDP and Main Components (Output, Expenditure and Income). https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=namq_10_gdp&lang=en (accessed April 05, 2018).
[6] **European Central Bank.** 2018d. Euro Area Bank Lending Survey. https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html (accessed April 04, 2018).



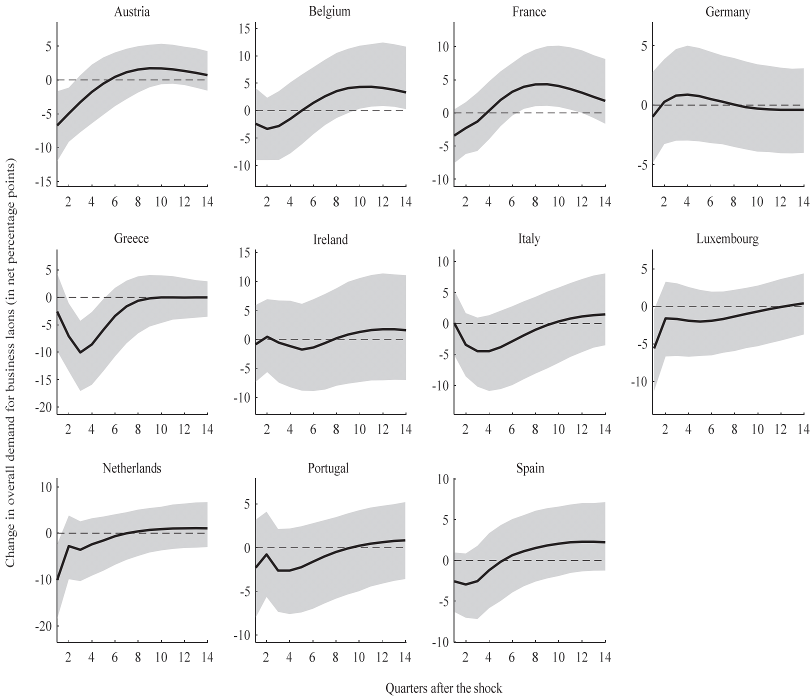
Notes: Overall demand for business loans (dl) and the (factor of) demand for business loans for fixed-investment financing (dl_fi) are expressed as a net percentage (see the specification of variables in Table 1).

Source: Drawn based on data from the ECB Statistical Data Warehouse (ECB 2018b).

Figure 1 Overall Demand for Business Loans and Demand for Business Loans for Fixed-Investment Financing

Model (1a) is estimated separately for each euro area country in the sample. Figure 2 presents the resulting impulse response functions of the overall demand for business loans (dl)

to a one standard deviation shock in uncertainty ($CLIFS$) over the period of 14 quarters from the shock. While the responses of other endogenous variables of model (1a) are not shown, it is notable that for all the countries except Austria, France, Ireland, and Luxembourg, it is found that an uncertainty shock results in a statistically significant decline in real GDP. GDP reduces the most in Greece, where the effect is also the most protracted. The results corroborate the findings from existing empirical literature (e.g. Bloom 2009; Colombo 2013; Baker, Bloom, and Davis 2016; Meinen and Roehe 2017). It is also found that an uncertainty shock does not significantly affect the price level, except in Germany where the price level drops to the uncertainty shock. The interest rate for business loans significantly reduces upon an uncertainty shock, except in Greece, Ireland, and Portugal.



Notes: The impulse response functions of the overall demand for business loans (dl) to a one standard deviation uncertainty shock ($CLIFS$) over a period of 14 quarters from the shock are shown, based on the results of model (1a). The shaded area represents a 95% confidence interval. The lag length of the Bayesian VAR model (1a) for Austria, Belgium and Germany is 1, for France, Italy, Luxembourg, the Netherlands, and Portugal it is 2, for Greece and Spain it is 3, and for Ireland it is 4. As previously noted, following the arguments of Sims, Stock, and Watson (1990), impulse responses are valid also in the case of non-stationary variables. Luetkepohl (2011) further notes that the asymptotic properties of impulse responses even hold for unstable VARs (as found in this study for models (1a) and (1b) for the Netherlands) if the order of the model is larger than 1.

Source: Own calculations.

Figure 2 Change in the Overall Demand for Business Loans in Response to an Uncertainty (CLIFS) Shock

Turning now to the results of the main interest of the paper, as depicted in Figure 2, an uncertainty shock results in a significant short-run decline in the overall demand for business loans (dl) in only four out of 11 countries: Austria, Greece, Luxembourg, and the Netherlands.

In Greece, for instance, three quarters after a one standard deviation increase in the uncertainty indicator, a decline of approximately 10 net percentage points in the overall demand for business loans is observed. The contractual effect fades a few quarters after the shock (in Austria and Greece) or sooner (in Luxembourg and the Netherlands). In the medium term, the demand for business loans rebounds, which is especially noticeable in France where the demand for business loans significantly improves six quarters after an uncertainty shock. This pattern of response to an uncertainty shock is explained by Bloom (2009), who notes that in the medium term, a surge in uncertainty "induces an overshoot" in economic activity. In turn, this may lead to an increase in the demand for business loans. These results are robust to the reordering of variables: the interest rate was placed to the penultimate place (the results are not shown).

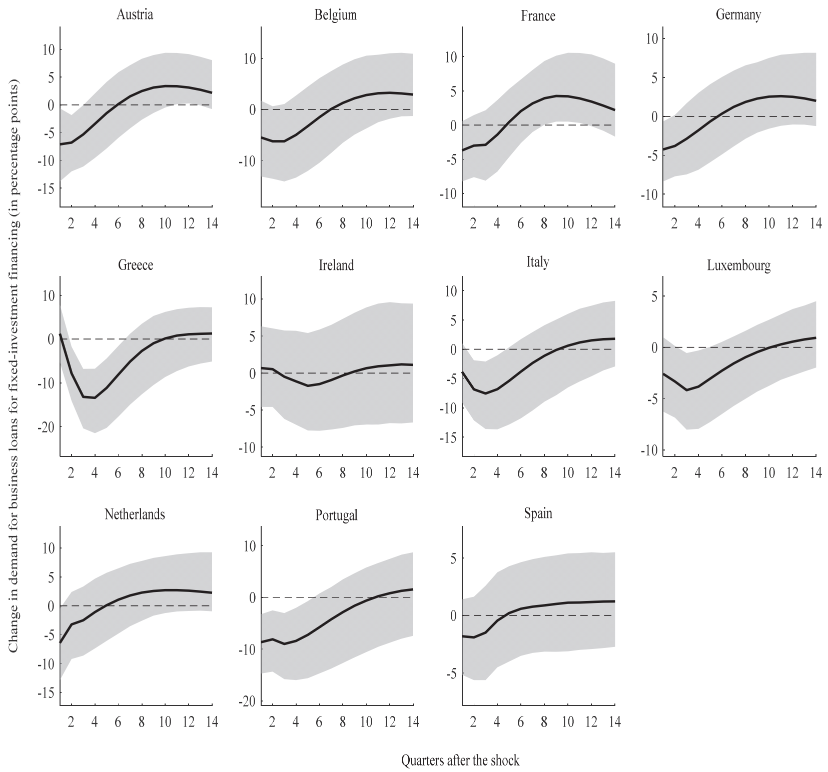
Although the existing literature provides an explanation for why uncertainty shocks can be expansionary for the demand for business loans (the Oi-Hartman-Abel effect), the finding that the demand for loans declines significantly in only four of the 11 euro area countries is somewhat surprising given that the majority of empirical studies find the uncertainty shocks have a negative effect on (macro-)economic activity. In this respect, it must be stressed that Figure 2 traces the effect of uncertainty shocks on the overall demand for business loans, including the demand for fixed-investment financing, the demand for financing working capital and inventory, and other motives (see Köhler-Ulbrich, Hempell, and Scopel 2016; ECB 2018b); or any issue of the EABLS). The literature (see Literature Review) gives contradictory conclusions for the response of demand for loans for fixed-investment financing to uncertainty shocks.

To shed some light on this issue, the next focus of this study is on the demand for business loans for fixed-investment financing, thus estimating model (1b). The resulting impulse responses are illustrated in Figure 3. A comparison of Figures 3 and 2 shows that across the investigated euro area countries, an uncertainty shock generally results in a larger decline in the demand for business loans for fixed-investment financing than in the overall demand for business loans. It is also notable that in Figure 3 the impulse response functions are statistically significant for more countries than in Figure 2. A decline in the demand for business loans for fixed-investment financing as a result of an uncertainty shock is statistically not significant only in Belgium, France, Ireland, and Spain. The largest effect is observed in Greece, where an uncertainty shock leads to a reduction in demand for business loans for fixed-investment financing by up to more than 10 net percentage points, followed by Portugal and Italy. The demand for business loans for fixed-investment financing improves after few quarters from the shock, the most slowly in Greece, Italy, and Portugal. The findings of this study thus support Balke and Zeng (2013), who report that the demand for loans responds negatively to an uncertainty shock. Their study, however, investigates the overall (business and household) demand for loans, while this study concentrates on the demand for business loans.

The results of this study indicate that once we concentrate on the demand for business loans for fixed-investment financing, uncertainty shocks in the euro area seem to transmit to the demand for business loans primarily through the channels of imperfect credit markets, real options, and precautionary saving (which, as discussed in Literature Review, theoretically explain the negative response of the demand for loans to the shock).

The results of this study corroborate the findings from literature (e.g. Arellano, Bai, and Kehoe 2012, 2016; Balke and Zeng 2013; Christiano, Motto, and Rostagno 2014; Gilchrist, Sim, and Zakrajsek 2014; Bonciani and van Roye 2015; Pirozhkova 2017) that the bank loans market is important in the transmission of uncertainty shocks. Uncertainty affects loan supply, as noted by e.g. Balke and Zeng (2013) and Valencia (2017), and, as the results of this study demonstrate, also the demand for business loans, especially for fixed-investment financing.

Two important economic policy implications of the results can be stated. Economic policy should closely monitor uncertainty (CLIFS in this case) to prevent or dampen its negative economic effects (see e.g. Bloom 2014; Ferrara, Lhuissier, and Tripier 2017). Additionally, because the bank loans are the prime source of external financing for the euro area business sector (see e.g. World Savings and Retail Banking Institute and European Savings and Retail Banking Group 2015; ECB 2016), and thus potentially play a major role in monetary policy transmission (see e.g. Leonardo Gambacorta and David Marques-Ibanez 2011; Dajčman 2016), the knowledge of how uncertainty affects the demand for business loans may be relevant from a monetary policy perspective (see e.g. Knut Are Aastveit, Gisle James Natvik, and Sergio Sola 2013 for how uncertainty affects monetary policy).



Notes: The impulse response functions of the demand for business loans for fixed-investment financing (dl_fi) to a one standard deviation shock in uncertainty ($CLIFS$) over the period 14 quarters from the uncertainty shock are illustrated based on the model (1b) results. In model (1b), the number of lags for individual countries are: 1 for Austria and Germany, 2 for Belgium, France, Italy, Luxembourg, the Netherlands, and Portugal, 3 for Greece and Spain, and 4 for Ireland. Alternative lag specification (1 and 2 lags, respectively) was also estimated and the presented findings from Figure 3 remain robust, except for Belgium, where in the model with 1 lag the impulse response becomes significantly negative only shortly (at 2 quarters after the shock) (the results are not shown).

Source: Own calculations.

Figure 3 Change in Demand for Business Loans for Fixed-Investment Financing in Response to an Uncertainty (CLIFS) Shock

4. Conclusion

This paper used the Bayesian VAR technique to analyze the effect of uncertainty (measured by CLIFS) shocks on the overall demand for business loans and the demand for business loans for fixed-investment financing, respectively, both taken from the EABLS, for 11 euro area countries. The results show that in 4 countries the uncertainty shocks lead to a decline in the overall demand for business loans and in a greater number of countries to a decline in the demand for business loans for fixed-investment financing. Greece is found to be impacted the most.

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