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Determinants of lending activity in the Euro area

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Abstract

Empirical estimations of the drivers for loan extension mainly apply the outstanding stock of bank credit as the dependent variable. This paper picks up the critique of Behrendt (2016), namely that such estimations may lead to misleading results, as the change of the stock is not only driven by extended loans, but also by repayments, write-downs, revaluations and securitisation activity. This paper specifically applies a variable of new credit extensions for eight Euro area countries in a simultaneous equation panel model to evaluate potential determinants for credit extension, and compares the findings with a conventional specification using the outstanding stock. It is found that the new lending variable performs exceedingly better in respect to the underlying theory than the stock variable. This result has vast implications for the conduct of monetary policy while looking at credit trends. As most determinants have different coefficients, not only by magnitude, but also by significance and sign, central banks might react in a different way to changing trends in lending when looking at the stock variable rather than the underlying credit extension.

Keywords: credit channel, monetary transmission, bank lending
JEL Classification: C18, C82, E51, E52

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1 Introduction

Empirical models of determinants of bank lending mostly apply the change in the outstanding stock of credit as the dependent variable. This approach might be prone to inaccuracies. In Behrendt (2016) it is argued that to understand the transmission of monetary policy shocks and what determines credit extension, one should look at the amount of new lending in the economy, rather than the stock of credit. By taking the outstanding stock of credit, empirical estimations might be distorted because of the inclusion of other factors in the stock variable, namely repayments, write-offs, securitisation activity and revaluations, over which the central bank has almost no influence and are in part not attributable to economic developments, but are quite random (like f.e. the length of the loan contract, which has an impact on the speed of repayment). The following paper tries to take this argumentation to the data and estimates to which extend determinants of bank lending differ in regard to the model set-up.

For this, different empirical models are applied. Estimations using the amount of new lending, proxied by new business volumes from the Monetary and Financial Interest Rate (MIR) statistics of the European Central Bank (ECB), are compared to estimations applying the outstanding stock of credit. Due to the different behaviour of these two time series, it can be expected that the specific estimation coefficients vary in their significance, magnitude and possibly in sign. This would have important consequences for the conduct of monetary policy, and could lead to a more robust estimation of monetary policy transmission through the credit channel.

In most empirical analyses the log change in the outstanding amount of credit in an economy is applied as the dependent variable, while mostly modelling AR(1) processes, with various supply and demand side determinants as independent variables. What is found in the literature is that there are certain bank and macro specific variables which determine bank lending in the aggregate. Generally, economic performance and inflation dynamics (past and expected) affect lending positively (Bernanke and Blinder (1988)). These are mainly determining factors for the demand side, while bank specific factors play a crucial role for the supply of bank loans. Kashyap and Stein (2000) and Kishan and Opiela (2000), among others, show that more well capitalised, less leveraged and more liquid banks have a higher lending capacity and react to tightened monetary policy less severely, by shrinking their lending volumes less drasticly.

Most of these earlier studies rely on single equation estimations to capture the effects on bank lending. While these studies reveal the impacts of different determinants on final bank lending, they cannot show to which extend supply and demand effects affect the market outcome. It would be preferable to apply micro banking data to this problem (like f.e. Jimenez et al. (2014)), but this is not possible for the whole Euro area, since the ECB does not collect data in an European-wide credit register, like for example available in Spain or Italy. Therefore, this paper has to draw back on aggregate data and model the empirical estimations for the demand and supply side in two different equations using 2SLS and 3SLS set-ups, thereby taking into account the simultaneous behaviour of restrictions to bank lending on both market sides (see f.e. Carpenter et al. (2014)).

What is found in this paper is that it does indeed make quite a distinct difference which credit variable is applied, as could be expected by the different behaviour of the change in the outstanding stock of credit in comparison to the underlying movement in new credit extensions. Not only do the magnitudes of the estimated coefficients differ, also significances and even the sign of the coefficients may change. This result has serious implications for the conduct of monetary policy, as central banks might react to changing credit conditions in a different—and maybe not justified—way while looking at the stock data, given the underlying trends in new credit extensions.

The paper is structured as follows. The second section gives an overview of the empirical literature of the bank lending channel, with a special focus on what determines bank lending. The empirical model is then presented in the third section. The crucial determinants, which are applied in the different specifications, are motivated there. In section four the different empirical models are estimated. Thereby, first a simple AR(1)-estimation for the whole Euro area, similar to the prevailing literature, is carried out, to reveal if there are indeed differences using the specific credit variables. In the second part of this section, a more rigorous regression, using panel data of 8 Euro area countries to account for the specific country effects, is conducted. Therefore, a two equation simultaneous estimation is carried out, to estimate the impact of certain supply and demand determinants separately. Section five concludes.

2 Literature review

The analysis of monetary policy effects on the mechanisms of the credit channel face two crucial problems. The first refers to how banks are able to insulate their loan portfolio from monetary policy shocks. The main analysis here deals with the question on how banks can adjust their internal funds in a way to not be affected negatively to a changing monetary policy stance. Second, from an economical point of view it is quite complicated to disentangle demand from supply side factors in credit markets. The question here is, if a reduction in lending stems from a reduction in loan demand or from a decline in loan supply (see Peek and Rosengreen (2013) for an overview).

Regarding the first issue, evidence of empirical studies on the adjustment process of the loan portfolio of banks towards a monetary policy shock show that monetary tightening leads to a reduction in the asset portfolio through shrinking securities. Only with a delay a reduction in lending sets in (see Bernanke and Blinder (1992)). Although some studies find an increase in lending in the short run (f.e. Morgan (1998), Ivashina and Sharfstein (2010)), this can be traced back on the delayed response of the loan portfolio, as the negotiation process of credit extension is generally quite long. Furthermore, lenders have concerns to access credit in the future, whereby they draw down on loan commitments and previously established lines of credit. But in the longer-run the decrease in loan supply should outweigh demand reactions.

Banks who can respond to monetary policy tightening by raising non-reservable liabilities are less affected as other banks, and therefore do not shrink their loan portfolio as much (Kashyap et al. (1996)). Kashyap and Stein (2000) show that more liquid banks have easier access to external financing and can thus insulate their loan portfolio with more ease to a monetary tightening. Therefore, less liquid banks and banks with an inferior capital base have to shrink their loan portfolios to a greater extend (see also Kishan and Opiela (2000), Peek and Rosengreen (1995)). Also, smaller banks are less likely to find alternative sources of funding, if not affiliated to a large multibank holding company (see Campello (2002)).

Since one cannot easily differentiate to which extend the change in the loan portfolio is attributed to supply or demand effects, recent studies try to draw on data on a micro level from detailed credit registers. These panel studies relate bank balance sheet data to other bank and firm specific characteristics. With regard to linking firm characteristics to loan supply, Jimenez et al. (2012b) find that short-term interest rates and loan approvals are negatively correlated, which is more pronounced with weaker bank health, especially in crisis times. Additionally, firm health also plays a restraining role in the supply of credit, as it has stronger effects on lending than bank balance sheet strength in crisis times. Ciccarelli et al. (2015) show that loan supply restraints are more pronounced than demand restraints following a negative monetary shock by using confidential bank surveys for the Euro area and the United States.

While micro level data linking firm to bank characteristics are not available for the whole Euro area, a different methodology of disentangling supply from demand effects is applied in this paper. As credit supply and demand are determined contemporaneously on one market, a simultaneous equation model using two equations is estimated. Therefore, an instrumental variable approach similar to Carpenter et al. (2014) and Calani et al. (2010) is applied. By using only one equation models (like f.e. Bernanke and Blinder

(1988)) it cannot be distinguished to which extend supply and demand factors react to changing economic conditions. Calani et al. (2010) show that loan demand is negatively influenced and supply is positively associated with the loan rate, which is in line with conventional theory.

Generally, empirical research finds evidence in the importance of the credit—and especially the bank lending—channel in the transmission of monetary policy. In addition to effects on the liability side through the standard interest rate channel mechanisms, there are significant effects through a restructuring of the asset portfolio of banks in response to a monetary tightening. Moreover, there is empirical evidence that liquidity and capital constrained banks react more severely to monetary policy shocks, as well as the adverse impact on bank dependent borrowers, with a more pronounced effect of supply over demand constraints.

On the demand side, expectations of future returns on investment play a crucial role for the debtor. If these are positive, loans are more likely to be repaid, which leads to a higher loan demand. These expectations are formed on the basis of past experiences, which are then updated into the future on the basis of recent data. Therefore economic growth is viable for the demand side decision to request loans (see Bernanke and Blinder (1988), Maddaloni and Peydro (2011)). Furthermore, inflation dynamics play a role in the credit demand decision, as with c.p. higher inflation debt looses its worth more quickly, therefore loans can be repaid quicker, which would lead to higher loan demand.

One problem with the empirical research, with an exception of recent studies using data from detailed credit registers, is that they still incorporate balance sheet data of loans, and the results are therefore prone to distortions due to the incorporation of factors in the change of the outstanding stock which are not reflecting the underlying trends in credit extension (see Behrendt (2016) for a detailed analysis of this critique). The following empirical application of data on new lending tries to remedy this deficiency.

3 Empirical Model

3.1 Methodology

There is one particular issue with using aggregate data on lending, because of which the use of detailed data from explicit credit registers would be preferable. While applying aggregate lending data, only the amount of actual new lending is quantifiable. This final amount is therefore only the result of the minimum of supply and demand decisions on credit markets. But given the question of the paper, that it shall be shown which are the determinants that influence loan supply and demand, one would have to apply more profound data of the notional plans, and not only on the final, realised amounts. As loan requests which were rejected are not visible in the aggregate credit data, it cannot be seen which market side was the constraining one. Although new lending data of the ECB, as well as data of the outstanding stock of credit, cannot account for this critique, data on credit extensions certainly represents the conditions on credit markets better than data of the outstanding stock of credit in an economy.

The empirical estimation in this paper tries to account mainly for the identification issue prevalent in the literature. The bank specific internal adjustment cannot be analysed in this macro setting and is therefore left out.[1] Additionally, the critique of Behrendt (2016) is taken up again, where it is argued to use data on new lending activity in empirical estimations of determinants of lending activity. The strategy is to estimate the model twice. Once with the new lending variable and a second time with the change in the stock as the dependent variable, respectively, to examine to which extend empirical investigations might differ with a more precise variable for new lending activity. In a first step, a standard single-equation autoregressive model, as prevalent in the literature, will be estimated for the Euro area to compare the results with other empirical studies, while in a second step a more sophisticated simultaneous equation panel model will be estimated for 8 Euro area countries.[2]

Along the lines of recent literature (see f.e. Carpenter et al. (2014), Calani et al. (2010)) supply and demand equations are estimated separately in the panel model, due to the simultaneity of the formation of loan rates, as the most crucial variable for both supply and demand decisions on lending. Following the literature on bank credit determinants, specific variables, which are important for the supply and demand side, are controlled for, notably macroeconomic determinants, expectations of future economic performance, and financial market and bank specific determinants, like the policy rate, stress indicators, bank balance sheet determinants and survey based data on lending standards of banks (see f.e. Ciccarelli et al. (2015), Everaert et al. (2015), or Maddaloni and Peydro (2011)).[3]

[1] The reader shall be referred to the micro bank level literature like Abuka et al. (2015), Jimenez et al. (2012a), or Jimenez et al. (2014).

[2] The countries are Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. The sample had to be restricted to these eight countries because of data availability.

[3] Due to the nature of the aggregate data, this study cannot reveal the specific bank reactions in their loan supply to changing economic conditions, but merely shows a country wide aggregate, which is prone to outliers. Therefore, the estimates shall not be interpreted as a direct reaction function under which condition a specific bank grants a new loan application, but rather be seen as an industry wide response to changing conditions. Nevertheless, valuable information as to which extent market

3.2 Supply Factors

Commercial banks try to maximise their profits while taking into account several constraints, which are specifically funding, liquidity and capital constraints, while simultaneously managing their optimal asset structure given the macroeconomic environment (see Mishkin (2012)). In their supply decision of additional credit, banks have to weigh the revenues of an additional credit against the costs. The loan rate of extended credits is the determining revenue factor for a bank, and will be modelled on the supply side as the revenue factor. Higher loan rates would be expected to lead to higher credit supply, as—if one abstracts from any market frictions—there would be higher margins available, which would result in a better profit outlook.[4]

On the other hand, banks face costs for refinancing, and are subject to capital and reserve requirements. A proxy for the costs of refinancing can be the policy rate, for which banks have to refinance themselves to meet specific requirements. Higher policy rates should suppress loan supply, because of higher costs for refinancing. Additionally, the policy rate can also be seen as a proxy for future economic conditions, respectively expectations about the future path of the policy stance. Upward deviations would lead to expectations about a slower future growth path of the economy, which would also lead to lower credit extension.

Furthermore, bank balance sheet specific determinants are analysed. The literature shows that well capitalised and liquid banks are more likely to extend loans. Therefore, the capital ratio and liquidity measures are added to the estimation. These should have a positive effect on bank lending. Anyway, identification becomes a bit difficult, since only aggregated data is applied in this study, which is therefore prone to outliers. Additionally, the capital ratio might also cause some problems in this estimation, since during the estimation period the Basel regulations were extended further, requiring banks to hold more capital. The capital ratio might therefore be vulnerable to estimation biases, and higher capital ratios might not directly be attributable to a higher capacity to extend loans. Although this problem might be mitigated while using a broad capital definition

conditions affect bank lending can be drawn from this method. Additionally, while the incorporation of the specific determinants are motivated by micro level considerations, they are also valid at the aggregate level.

[4] While an individual higher loan rate could also be the result of higher risks of loan extension for the bank, this might not be a big concern in the instrumental variable set-ups, because movements of the loan rate due to higher risk perceptions are removed in the first stage regression by incorporating risk measures.

as applied here, since the requirements for total capital were already at 8% since the introduction of Basel I in 1992 and were not raised during the observation period.[5] While there is a markedly increase in (especially risk-weighted) capital visible after the Lehman crash in 2008, this is not per se due to the higher capital requirements of the Basel regulations. It is mostly due to market discipline effects and to self interests of the banks, as only the capital ratios in respect to risk weighted—and not total—assets increased after the financial crisis (see Brei and Gambacorta (2014)). Anyway, it can be that since during this period bank lending declined, the estimation could potentially show a negative relationship with regard to new lending. Moreover, banks with higher credit exposure are less likely to extend further loans. Therefore, the loan ratio is added as an additional supply side variable, which should have a negative impact on loan supply. While these arguments mainly stem from micro level analyses, they are generalisable to the aggregate level. A better capitalised and less leveraged banking system would lead to lower risk exposure for the individual institute and would in general result in a higher capacity to extend loans for a specific bank.

Additionally to the individual banks' risks, market risks also play a determining factor in loan supply decisions. These risks lead to a reduction in loan supply, since average real returns shrink, and it becomes less attractive for banks to extend loans. The market risk is modelled by the Composite Indicator of Systematic Stress (CISS) of the ECB (see Holló et al. (2012) for an overview of this indicator). The general CISS is an aggregation of 15 indicators, which covers risks in 5 markets—money market, bond market, equity market, the foreign exchange market and risks for financial intermediaries. For the panel model the Sovereign CISS indicator has to be used, as the general CISS is only available for the whole Euro area. The Sovereign CISS compiles spreads and volatilities from the short (2 year) and long (10 year) end of the yield curve.

It would be preferable to also incorporate data about the individual balance sheet risk of banks, and thereby applying the ratio of non-performing loans (NPL) to total assets as an individual's risk variable. Unfortunately such data is not available for the Euro area and NPL-ratios are therefore left out in this paper. However, it can be expected, that the CISS and NPLs are highly correlated, since higher market risk would lead to more loan failures. Therefore, the CISS can also be seen as a noisy proxy for balance sheet risk.

[5] Nevertheless it might be appropriate to apply a dummy for the Tier 1 capital requirements, but since the requirements for the Basel I and II were all risk weighted, it is difficult to ascribe a numerical value during the early observation period and is therefore left out here.

As Lown and Morgan (2006) and Ciccarelli et al. (2015), among others, note, information from survey data can contain valuable information about changes in lending standards of banks. The ECB performs the Bank Lending Survey (BLS), where they ask senior loan officers about changes in their lending practices (see Ciccarelli et al. (2015) for a detailed explanation of the methodology). In this paper, past developments are of interest. Therefore, backward looking questions for changes in the lending standards are taken. What can be expected is that with tighter lending standards, loan extension decreases, and vice versa.

3.3 Demand Factors

The loan rate constitutes the main determining factor on the demand side as well. It represents the cost of lending for borrowers. The decision to demand loans is based on the net return of investments with respect to the interest of loans on the one hand and, once the investment decision is made, on the costs of alternative financing (like bond issuance) on the other. A higher loan rate would suppress loan demand, as lending gets more costly with respect to other forms of financing and therefore becomes more unattractive.

Additionally, macroeconomic conditions need to be incorporated to adequately capture loan demand from the public. Borrowers look at previous economic conditions, from which they draw on expectations about the future. Furthermore, good economic conditions in the past mean that borrowers are more confident to request a loan, as their likelihood to repay a loan is stronger if they faced better economic positions in the past.

On top of that, expectations about future economic conditions play an important role on credit demand. Better expectations for the future would also lead to more confidence to repay a loan and would therefore strengthen demand. Thus, lagged economic growth and lagged inflation dynamics are modelled as backward-looking variables, while survey data on the expected future path of economic growth and inflation expectations are used as forward-looking indicators. It can be expected that demand responds to all these variables in a positive way.

Information from the BLS are also modelled for the demand equation. Replies to the question of the change in the demand for loans and credit lines at banks are captured here. Higher demand visible at the banks should also translate into higher credit creation, absent supply constraints.

3.4 Data

To be in line with the literature, the logarithmic change in the amount of loans extended by Monetary Financial Institutes (MFIs) vis-a-vis the Euro area (excluding ESCB) are taken as reference here.[6] To account for the critique on the use of the stock variable, data from the MIR statistics of the ECB is applied for new lending, although it has some shortcomings. The ECB collects data of "new business volumes" as weights for the calculation of the aggregated MFI Interest Rates, i.e. the average interest rate which creditors have to pay for a new loan. To not over-differentiate, the simple logarithmic change is used, as new lending is a flow variable in itself. To have the estimation technique correspondingly, the second order change in the log of the outstanding amount of bank credit is additionally applied in a further model (see Biggs and Meyer (2013), Huang (2010) for a reasoning on this).

The main independent variable is the loan rate, as collected in the MIR framework. The loan rate is a determining factor for both market sides, as it is a revenue factor for the supply and a cost factor for the demand side. Since the loan rate is only collected for different sub-groups, these individual loan rates are multiplied by the proportion of the respective loan category with respect to the whole amount of new business loans.

To account for a varying monetary policy stance, the change in the policy rate is applied on the supply side, to cover the forward looking aspect of banks in their decision to extend loans. For this, the one quarter lagged change in the real EONIA rate, which is the average overnight rate for unsecured interbank lending, is used in the model. This is in line with standard macroeconom(etr)ic models (see Ciccarelli et al. (2015) for a reasoning as of why the EONIA rate might be an appropriate variable for the stance of the monetary policy even during the financial crisis). A tightening of monetary policy would lead to expectations about slower economic growth, which would then induce banks to cut back on lending. It can therefore be expected that the change in the policy rate is negatively correlated with the growth of lending.

For the market risk, the Composite Indicator of Systemic Stress (CISS) of the ECB is taken. The sovereign index is applied in the panel model. In time of economic stress, this index rises. Therefore, the CISS is to be assumed to be related negatively to bank loan supply, as in time of stress it can be expected that credit extension falls due to uncertainty

[6] Data definitions, sources and the expected signs can be found in table 1 in the appendix, while summary statistics are found in table 2 in the appendix.

about the future path of the economy and due to possible arising balance sheet stress for the banks, which would then depress bank loan supply.

Bank balance sheet specific determinants are added to the supply side equation. The amount of securities and cash to assets is used as a liquidity indicator (see Gambacorta and Marqués-Ibáñez (2011)).[7] It can be expected that higher liquidity in the banking sector leads to higher loan extension. The same applies for better capitalisation in the banking system. To capture bank capitalisation, a capital ratio is calculated, as the ratio of capital and reserves to total bank assets (see Gambacorta and Shin (2016)). As a risk variable for the loan portfolio, the outstanding stock of credit in relation to total bank assets is calculated. This loan ratio is expected to have a negative effect on bank lending, as higher leverage in the economy might induce banks to cut back on lending, because of internal balance sheet weakness and because of a possible over-leveraging in the private sector. Contrary, a positive sign may be the result of credit trends reinforcing themselves in the light of good or bad economic conditions.

In the demand equation, past and expected future economic activity is modelled. Annual GDP growth is taken as a proxy for past performance. The majority of other studies use the log difference of economic growth. But since the private sector is mainly focussed on annual growth rates, as being the most visible published source, it is taken here to reflect the decisions of private sector agents better (see also Ciccarelli et al. (2015)). Due to the delayed publication of the quarterly growth data and to account for the duration of the loan application process, GDP growth is modelled with a 3 quarter lag. This is in line with the literature (see Carpenter et al. (2014)). Additionally, the choice of the lag length is also confirmed by looking at the cross-correlations between GDP growth and new lending growth. For forward looking economic trends, business confidence is modelled. Therefore, the log change in the Economic Sentiment Index (ESI) is used, which is compiled through a survey undertaken by the European Commission to capture expectations for future economic activity in the private sector (see European Commission (2016)).

Inflation dynamics also play a role in the decision of loan demand. With higher inflation, nominal debt looses its worth more quickly and private sector's agents can

[7] It can also be argued to model excess reserves additionally to cash and securities, as these are also indicators for liquidity. Especially after the financial crisis the ECB used unconventional monetary policies to guarantee enough liquidity for banks by issuing more reserves than necessary for the maintenance of required reserves. Additional specifications will be estimated using also excess reserves due to this reasoning.

therefore delever faster. This might induce higher credit demand. For the backward-looking behaviour, the headline inflation rate is applied with a one quarter lag. The same rationale as with GDP growth also applies here. Inflation expectations from the Survey of Professional Forecasters (SPF) of the ECB are taken as the forward-looking inflation determinant in the autoregressive model, while inflation expectations from the consumer surveys of the European Commission are applied for the panel models, because the SPF data is only publicly available for the Euro area as a whole. From the SPF data, the expectations 24 months in advance are taken.[8] The European Commission gathers data about the one year ahead price dynamics.

For the survey data on bank lending standards, the changes in the demand for loans are captured in the demand equation (question 4 in the BLS), while taking the change in the credit standards of banks (question 1) for the supply side equation. The demand variable shows the difference between banks reporting an increase and a decrease in loan demand. Therefore, positive values indicate higher demand for loans. On the supply side, the BLS data is calculated as the net percentage of banks answering that they have tightened credit standards minus banks reporting an easing. Positive values therefore show a tightening in credit supply. Thus, for the demand side a positive sign would be expected with regard to loan demand and a negative sign for the supply side BLS variable.

The variables on the supply side (except for the policy rate) are captured without a lag, since banks have data about their balance sheet strength contemporaneously available while extending loans. However, there might be methodological problems, especially with regard to business loans. As the main question in this paper is what determines the decision to request or extend a loan, respectively, one would need to apply the prevailing data at the time of the inquiry on the demand side and on the final decision by the bank on the supply side. Micro banking studies looking at applications from detailed credit registers can capture this due to the availability of the specific dates of the request more stringently. With aggregate data, this cannot be modelled specifically. In regard to the supply side, especially for established credit lines to businesses, one does not know when the underlying loan contract between the bank and the private sector agent was finalised. Since it can be that these loans sit idle for months and only get drawn in the future, the underlying economic trends might have changed in the meantime.[9] Additionally, there is

[8] Results do not vary significantly when taking the 12 month ahead inflation expectations.

[9] Using U.S. data, it can be seen that the average length between the date when the terms are set and the date on which the loan is drawn is around 12 months for commercial and industrial loans.

a time gap between the application for a loan and the final decision of the bank, as the process often takes some time. These issues cannot be accounted sufficiently in model set-ups using aggregated data. But, by using quarterly data, they can be mitigated to a certain extend.

4 Empirical analysis

The empirical approach is twofold. First, a comparison of a simple AR(1)-model using the change in the credit stock as the dependent variable, with a model set-up using the new lending variable for the whole Euro area, is carried out. From this, a general comparison can be conducted to detect if and to what extend estimations using the different credit variables might deviate. In a second step, to account for the simultaneity of credit supply and demand, a simultaneous equation panel model for 8 Euro area countries is estimated using different instrumental variable approaches.

4.1 Autoregressive model

Most empirical studies try to determine factors for bank lending, both panel and aggregated data, apply single equation autoregressive models with the logarithmic change in the outstanding stock as the dependent variable (see f.e. Bernanke and Blinder (1988), or Garcia-Escribano (2013)). In addition to several determining factors, as discussed in the last section, one lagged term is included on the right hand side equation, due to the autoregressive behaviour of the outstanding stock.

In accordance to the prevailing literature, a typical AR(1)-model could therefore be specified as follows:

$$\begin{aligned} \Delta logLoanStock_t =& \beta_0 + \beta_1 \cdot \Delta logLoanStock_{t-1} + \beta_2 \cdot LoanRate_t + \\ & \beta_3 \cdot \Delta PolicyRate_{t-1} + \beta_4 \cdot MacroVariables_t + \\ & \beta_5 \cdot BankVariables_t + \beta_6 \cdot SurveyData_t + \epsilon_t. \end{aligned} \tag{1}$$

This single equation model with the change in the outstanding stock as the lending variable is compared to models using the new lending variable and additionally—to account for the autoregressive behaviour in the stock variable—the second difference of the outstanding stock (see Huang (2010) for a reasoning on this). There is no AR-term in the new lending models, since the change does not exhibit an autoregressive pattern, as unit-root tests do not give rise to this assumption. For the stock variable, unit-root tests reveal that it is integrated of order one, therefore the second difference of the stock is stationary. All models are estimated using aggregated Euro area data from 2003Q3 till 2014Q2, with the data being described in section 3.4. To capture the impact of the financial crisis, a set-up with a dummy variable is used for each model. This variable is set to zero before the third quarter of 2008 and to one afterwards, as breakpoint unit-root tests indicated a breakpoint in the third quarter of 2008. Since the specific results are not that important and to prevent over-fitting the model, only a reduced form equation is reported here, as the main takeaway should be on how the choice of the variable affects the results. Therefore, bank specific variables are left out in this example. This also applies to the inflation variables.

Table 3 in the appendix shows the results for the autoregressive model using the outstanding stock of credit in models (1) and (2), and the OLS models using new lending in (3) and (4) and the second difference of the stock in (5) and (6). From the different estimations it becomes apparent that the results vary considerably with the choice of the credit variable. Signs and significances are prone to change with regard to the specific variables. Higher economic activity (past and expected) for example would have a negative impact on the stock. This appears implausible in the regard that a positive economic outlook should induce more credit extension, and a reinforcing effect of lower write-downs and higher upward revaluations in the outstanding stock would be expected on top of that (see Behrendt (2016), section 3 for an in depth analysis of this argumentation). While looking at the new lending variable, the expected positive sign for past GDP performance is found. The supply side BLS variable, which in theory should have a negative sign, is positive in the stock models (1) and (2), while being negative, as expected, in the new lending models.

It might be suspected that the models are prone to a regime change because of the financial crisis after 2008. This is not evident in the data. Although the dummy variable for the break in 2008 has the expected negative sign, it has no significant effect on the results of the other variables. The reason may be that the CISS already accounts for most of the impacts of the financial crisis. Consequently, it will be left out of the main equations in the panel model.

Apparently the autoregressive term in models (1) and (2) is highly significant and close to one, which would call for a higher order of differencing. This is done in models (5) and (6). Signs and significance levels are also not in line with the theory in these models. The BLS demand variable for example shows a negative sign (i.e. higher credit demand in banks would lead to a slower growth in the outstanding credit stock) in this specification, which can hardly be explained by theory.

In general, interpretation of these results is difficult, since both demand and supply determinants are modelled in one equation, where the specific effects for each market side cannot be analysed sufficiently. This would be especially vital for the interpretation of the coefficient for the lending rate, which is positive in almost all models. The positive sign implies that the expected positive supply effects exceed the negative effects on the demand side. But one cannot depict to which extend which side is impacting the final results. To differentiate which specific determining variable is affecting the respective supply and demand decisions for loan extensions, an instrumental variable approach, which is able to isolate supply from demand effects on the amount of lending and the corresponding lending rate, is being conducted in the next section.

4.2 Panel model

To account for the simultaneity of credit supply and demand decisions and for the simultaneous determination of the loan rate, as it is present on both market sides, the typical AR(1)-model set-up is not sufficient for a thorough estimation of credit determinants on both market sides. Therefore, a two equation model is analysed for 8 Euro area countries from 2003Q3 till 2014Q2. Through this, it is possible to isolate supply from demand effects (see Greene (2012), chapter 15). The model is then specified as follows:

Demand Equation:

$$\begin{aligned}\Delta logLoans_{1it} =& \beta_0 + \beta_1 \cdot LoanRate_{it} + \beta_3 \cdot Growth_{it-3} + \\ & \beta_4 \cdot Inflation_{it-1} + \beta_5 \cdot EconomicExpectations_{it} + \\ & \beta_6 \cdot InflationExpectations_{it} + \beta_7 \cdot BLSDemand_{it} + \alpha_{1it} + u_{1it}\end{aligned} \tag{2}$$

Supply Equation:

$$\begin{aligned}\Delta logLoans_{2it} =& \gamma_0 + \gamma_1 \cdot LoanRate_{it} + \gamma_2 \cdot \Delta rEONIA_{it-1} + \\ & \gamma_3 \cdot CISS_{it} + \gamma_4 \cdot Liquidity_{it} + \gamma_5 \cdot LoanRatio_{it} + \\ & \gamma_6 \cdot CapitalRatio_{it} + \gamma_7 \cdot BLSSupply_{it} + \alpha_{2it} + u_{2it}\end{aligned} \tag{3}$$

with β_i and γ_i as the to be estimated coefficients, α_{nit} as the country fixed effects and u_{nit} as the error terms.

Due to the simultaneity, an instrumental variable approach is applied using two stage least squares (2SLS), while treating the loan rate as the endogenous variable and regressing it over the included exogenous variables and the instrumental variables from the equation of the other market side in the first stage, to obtain the fitted value for the loan rate:

First stage regression:

$$\widehat{LoanRate}_{it} = \pi_0 + \pi_1 \cdot Z_{it} + \pi_2 \cdot W_{it} + \upsilon_{it} \tag{4}$$

where π_i is the unknown regression coefficients, Z_{it} are the instruments (exogeneous variables from the equation of the other market side), W_{it} are the exogeneous variables from the equation to be estimated and υ_{it} is an error term.

In the second stage, the estimate of the loan rate from the first stage is used as a regressor in each equation ((2) and (3) respectively) as the instrument and performing an OLS regression of the specific equation together with the included exogenous variables W_{it} (see Wooldridge (2002), chapter 5). By doing this, the fitted value of the loan rate from the first-stage regression is net of influences from the other supply and demand variables, and reveals the movements of the amount of lending resulting from the simultaneously determined loan rate, and is therefore not correlated with the disturbances anymore.

Furthermore, a simultaneous system model using 3SLS is estimated, with the third equation, (5), as the equilibrium condition (see Greene (2012), Chapter 10.6 for a discussion of simultaneous equation models). The logic behind this is that the amount of new lending is representing the quantity and the loan rate the price. The third equation is then equating supply with demand:

$$CreditDemand = CreditSupply. \tag{5}$$

The difference between the two instrumental variable approaches is that 3SLS contains an additional second step, where, after using the fitted values from the first stage (the same as in 2SLS), a consistent estimation for the covariance matrix of the equation disturbances is obtained, because of possible correlation of the disturbances across the two equations, therefore improving the efficiency of the estimator. The third stage then performs a GLS estimation instead of OLS estimation. A second difference is that while applying a 2SLS technique, not all exogeneous variables have to be used to obtain the instrumental values for the endogenous variables in the first stage, in contrast to the 3SLS set-up.

4.3 Panel results for new lending

The model analysed here is the one with the new lending variable. The results using the outstanding stock are discussed in the next section. The results from the main regressions using new lending are shown in table 4 for the demand side and in table 5 for the supply side in the appendix.

For each equation several model set-ups are considered. Model (1) in each equation shows a simple panel OLS model without restrictions. In column (2) country-fixed effects (α_{it}) are added. For column (3), time-fixed effects are considered, in addition to the country fixed effects. Columns (4) to (6) depict the results for the 2SLS IV approach, with the respective instrumental variables shown below the table, using country-fixed effects. The approach is to first use all exogenous variables in the first stage, and then to sort out the weak instruments and check for overidentification, until the "final" estimation in (6) is reached. Column (7) depicts the estimation for the 3SLS model.

The results show that it is indeed appropriate to use the instrumental variable approach to account for the endogenous behaviour of the loan rate. For both equations the expected signs are obtained, which is not the case for the OLS and the fixed-effects models, as the demand side estimates are positive there.

For the demand side, the loan rate only shows the expected negative signs in the IV specifications, and only being significant in models (6) and (7). Previous economic growth and inflation have a positive, mostly significant impact on lending, as expected.[10] Expectations about future economic trends exhibit no significance in determining lending for the more sparsely instrumented specifications, although they still have a positive impact on lending. Inflation expectations on the other hand reveal an ambiguous picture, having small estimates and no significance, except for the 3SLS model. The BLS data is positive and significant at conventional level, except for model (3) with time-fixed effects. Positive values for the BLS demand question stipulate a net increase in demand. Therefore, signs are as expected.

Turning to the supply side, the expected positive sign for the loan rate is observed. Higher loan rates therefore would lead to higher credit supply, as profit opportunities for banks might rise. Looking at the IV models, a rise of the loan rate of one percentage point would induce higher loan supply of at least 3.5 percentage points, with higher

[10] The results are robust even if the month-on-month change or different lags (1 or 2 quarters) for GDP growth are applied.

coefficients than the respective estimates on the demand side. This might explain the positive estimate in the single equation models (although they are not comparable one for one due to the different country sample and model set-up). The policy rate also has the expected sign and is significant of at least 10% in almost all IV specifications. Furthermore, the coefficient is also in the range (around -1.5) of other studies which try to find out to which amount a change in the policy rate accounts to a change in lending (see f.e. Gambacorta and Marqués-Ibáñez (2011), or Ehrmann et al. (2001)). An increase of the real EONIA rate of one percentage point would therefore lead to a 1.5 percentage point drop in the growth rate of new lending. The CISS also has the expected sign, with high significance of at least 10% in most IV estimations.

The IV models also support the assumption that higher liquidity in the banking sector contributes positively to higher lending.[11] Higher loan ratios happen to be negatively correlated with lending, but only showing a significant impact in the 3SLS model. The same applies for the capital ratio, although with the expected positive sign. The supply side BLS variable also has the expected negative sign (higher values for the BLS supply variable indicate tighter lending standards) for all models, with high significance of at least 5% in the IV specifications.

Additionally, using only loans to corporations as the dependent variable in the new lending set-up does not change the results substantially[12], except that the loan rate on the demand side becomes less significant in specification (5) and is positive in specification (4). This might be attributable to the more inelastic reaction of business lending towards loan rates, as the main rationale for credit demand lies in the immediacy of the investment decision and possibly in the long duration between the loan application and the draw down of the credit line. Therefore, different lags are added as a further robustness also for the previously not lagged variables, except the BLS data. Results do not vary significantly. Furthermore, what could also distort these results is the nature of corporate lending. Most short term loans are in the form of bridging loans, which are certainly very inelastic to the different determinants, as the immediacy of paying outstanding bills probably has higher priority and is very random. To eliminate these loans from the estimation would be preferable, but data about such loans is not available. Additionally, business loans can

[11] Adding excess reserves as an additional liquidity variable does not change the results. The estimation is robust with regard to the other variables, while excess reserves do not add any explanatory power to the estimation, as the coefficient is near zero with low significance.

[12] Detailed results are available from the author upon request.

be seen to be more pro-cyclical, which could mean that while loan rates rise because of a rise in the policy rate, the economy is still on a sufficient growth path, which would support credit extension.

As a preliminary conclusion, it can be assessed that the model with the new lending variable performs quite well, as signs and significances are predominantly in line with conventional theory.

4.4 Panel results using the Stock

Because of the autoregressive behaviour of the stock variable dynamic panel techniques have to be considered, using the change in the outstanding stock as the dependent variable in the panel set-up. Typically, a generalized method of moments (GMM) type estimation would be applied. Since these only lead to unbiased estimates for panels with a large number of individuals, several estimation techniques are considered here. Due to the autoregressive behaviour, a lagged term of the loan amount is included in the single differenced stock model (similar to section 4.1).

As a starting point, simple OLS regressions are considered. First without fixed effects (model (1), labelled OLS, in tables 6, 7 and 8), while adding country fixed effects in model (2) (labelled FE) (see equations (6) and (7)):

Demand Equation:

$$\Delta logLoans_{1it} = \beta_1 \cdot \Delta logLoans_{1it-1} + \beta_2 \cdot X_{1it} + \alpha_{1i} + u_{1it} \tag{6}$$

Supply Equation:

$$\Delta logLoans_{2it} = \gamma_1 \cdot \Delta logLoans_{2it-1} + \gamma_2 \cdot X_{2it} + \alpha_{2i} + u_{2it} \tag{7}$$

with X_{nit} being a matrix containing the independent variables, α_{ni} as the country fixed effect, and u_{nit} again as an error term.

Additionally, due to the simultaneity of the determination of the loan rate, the fixed effects model would need to be extended using an instrumental variable setting. This is done similar to the new lending panel model in model (3) here (labelled FEIV). The approach is the same as for the 2SLS models for new lending, with the loan rate as the endogenous variable, while using the exogenous variables from the other equations as instruments together with the exogenous variables of the same equation in the first stage.

Due to the lagged credit stock variable on the right-hand-side of the equation, OLS estimates can become inconsistent because of the correlation between the individual country effects and the lagged dependent variable. These should diminish with a higher panel length, but can nevertheless still be significant. The disturbances from country fixed effects can be eliminated using least square dummy variable estimates, but this estimation suffers from the small sample size (see Baltagi (2008)).

Due to this, dynamic panel techniques using GMM-type estimations are applied, to account for most of the shortcomings from the OLS estimations. However, they are designed for panels with many individuals, and therefore might still suffer from small-sample bias (see Judson and Owen (1999)). Nevertheless, two models using GMM estimation are considered here. First an Arrelano-Bond (AB) estimator is applied in model (4) (see Arellano and Bond (1991)). The first-differenced equation for this is given in equation 8 in a generalised form:

$$\Delta Y_{it} = \beta_1 \cdot \Delta Y_{it-1} + \beta_2 \cdot \Delta X_{it} + \Delta u_{it} \tag{8}$$

with ΔY_{it} as $\Delta logLoans_{it} - \Delta logLoans_{it-1}$.

Through first differencing, the constant country fixed-effect (α) disappears. For the estimation a GMM estimator with lagged-levels of the dependent and endogenous variables and first-differences of the exogenous variables in the levels equation have to be applied as instruments, because OLS would be inconsistent otherwise due to the correlation between ΔY_{it} and Δu_{it}. The differenced dependent variable in the levels equation is then not correlated with the error term anymore, and can therefore be used as an instrument.

But if the autoregressive process is too persistent, the lagged-levels instruments become weak. Therefore, a second GMM model (5) is estimated, using the modified Blundell-Bond (BB) GMM estimator. Here, a system GMM estimator with lagged first-differenced instruments of the dependent and endogenous variables in the levels equation in addition to the previously used lagged-levels instruments in the first-differenced equation is used (see Blundell and Bond (1998)). Both GMM models apply the same instrument set as the FEIV estimation.

To reduce the small sample bias, Kiviet (1999) proposes a least square dummy vector corrected estimator (LSDVC, model (6)), which performs better in terms of bias for models with a small number of individuals, than the GMM estimators for strictly exogenous regressors. For this estimation, the Anderson-Hsiao (see Anderson and Hsiao (1981)) estimator (AH) is applied to initialize the bias correction. This AH estimator lagges the dependent variable twice and uses it as an instrument for the first-differenced model with no intercept. Unfortunately, this estimation is not able to implement endogenous variables as instruments, which is a major drawback for the use in simultaneous model set-ups.

Although Monte Carlo tests reveal the most efficacy and accuracy for the LSDVC estimation regarding the lagged dependent variable and exogenous regressors (see Kiviet (1995), Judson and Owen (1999), Bruno (2005)), it does not account for the simultaneity of the estimation of the loan rate. Flannery and Watson Hankins (2013) account for endogenous variables in such simulations and show that some set-ups indeed exhibit significant errors. They show that fixed effects models have low errors for the endogenous variables, but not for the lagged dependent variable. On the contrary, the BB model is reliable regarding the endogenous and the lagged dependent variables. Due to the different drawbacks of each model for estimations with a small population, all six models are estimated and analysed (table 6 in the appendix depicts the specific drawbacks of each estimation more clearly). Tables 7 and 8 show the results for the stock estimations for the demand and supply equations, respectively.[13]

The same variable set-up as in equations (2) and (3) apply also for the stock model, with the added one period lagged credit variable on the right hand side of the equation. All instrumental variable approaches applied in the different stock models (FEIV, AB, BB) only use the smallest set of instruments, as in model (6) for the new lending variable, resulting in the use of the CISS for the demand side equation and the BLS Demand variable for the supply side equation. Results do not change significantly while applying different and/or more instruments, and are therefore omitted here.

It is apparent that the results differ considerably with respect to the results for the new lending models. Especially for the Blundell-Bond model (5), which is deemed to be the most accurate regarding the endogenous variable, the loan rate estimate differs quite substantially. The significant impact of the loan rate, as seen in the new lending estimations, also vanishes in the stock models, except for the FEIV model, which might perform with a low error in regard to the endogenous variable (see Flannery and Watson Hankins (2013)). Also, the negative impact of monetary policy decisions cannot be seen in the stock models, except for the FEIV model, but without being significant. This result might emerge because of the high inheritance in the stock, as new lending comprises only

[13] Arrelano-Bond tests for autocorrelation reveal a first-order autocorrelation structure throughout the GMM and LSDVC models, as expected.

a fraction of the outstanding stock (with the mean of this ratio being 6.7% between 2003 and 2015 in the Euro area on a monthly basis).

Additionally, the liquidity and capital ratio estimates are negative in the stock model for almost all specifications, which is not the case for the new lending models, and is hardly explainable by theory. Furthermore, the supply side BLS indicator becomes insignificant, although still exhibiting a negative sign. This might be due to the high inheritance of the stock, as changes in credit standards do not show up immediately to a large extend in the change of the stock. Although the sign and significance for the BLS demand question is still as expected, the magnitude is exceedingly smaller.

Further, it is also evident that the economic sentiment is far more significant for the stock variable than for the richer models using the new lending variable. The stock is to a large extend driven by other factors, in this case especially revaluations and write-downs, which fluctuate highly with economic activity and future economic expectations. As a consequence, this variable might not be optimal for analysing models which try to depict the rationale for loan extension. This seems to validate the argumentation from Behrendt (2016).

As in section 4.1 the stock model is also estimated with the second differenced outstanding stock variable.[14] Due to the stationarity of the variable, the same model set-ups as for the new lending variable are applied. What is apparent is that the models using the second differenced stock perform notably worse in regard to the underlying theory. Coefficients for the loan rate are negative in both equations, being even significant at the 5% level for the supply side IV models (5) and (6). The demand side variables (except inflation in the first 5 models) are positive, albeit mostly insignificant (except GDP growth for model (6) at the 10% level). On the supply side, all variables are insignificant, except the policy rate, which is positive throughout and significant at least at the 10% level in models (5) and (6), and the liquidity measure, which is negative throughout and significant at least at the 10% level in models (5) and (6). For these two models, the capital ratio also has a negative sign, while the BLS supply variable turns positive (estimations do not improve by taking other variables as instruments).

The second differenced stock model does not only perform poorly from the point of view that many estimates have signs which are not in accord to theory, it has furthermore little explanatory power. This observation gives more validation to the observation that

[14] Results are available upon request from the author.

the stock, especially here the change in the growth trajectory, is not suited to estimate determinants for new lending behaviour. This may be due to the reason that the other factors comprising the change in the stock hide valuable information about the underlying trends in credit extensions.

5 Conclusion

This paper takes the observations presented in Behrendt (2016) to the numbers. In this previous study, the observed differences between the behaviour of the outstanding stock of credit and data for new credit extensions gave rise to the hypothesis that empirical estimations of credit determinants might differ. As the question of the paper was to find out which variables determine loan extension to what extent, the conjecture from the observation of the stylised facts could be affirmed in the empirical part of this study.

Applying standard techniques using the change in the outstanding stock of loans as the dependent credit variable, past research found several determining factors to be important for credit extension. However, these estimations might be imprecise, given that the effect from the change in the outstanding stock may be distorted by repayments, write-downs, revaluations and securitisations. Therefore, a more thorough picture about what determines credit extension by applying data on new lending is given here.

For this, a comparison of empirical estimations using the outstanding stock on one hand and on the application of the new lending variable on the other is carried out. Although the estimations with the new lending estimate from the ECB MIR statistics suffer from a few shortcomings, they may give better insights into the factors influencing loan extensions.

Due to the simultaneous determination of the loan rate on both the supply and the demand side, single equation set-ups, as deemed reasonable in previous studies, seem not appropriate for such an estimation. Therefore, a simultaneous two equation panel model for 8 Euro area countries is estimated, using an instrumental variables approach. For the stock variable, dynamic panel techniques are considered as well.

While the models for the new lending variable mainly reflect estimates according to theory, the regressions for the stock reveal ambiguous results for some variables. What is especially striking is that the loan rate, which is seen as one of the major determining factors, has no significant impact on lending in the stock model (except for the fixed effects model using instrumental variables), while it is highly significant in the new lending model, especially for the supply side.

These differences in the estimations might have vast implications for monetary policy. If the central bank wants to react to certain economic events to anticipate future credit market trends in a way which is based on the estimations of a stock model, it might react differently to these, than if it would base it's policy on the estimates of a model using new lending. Reactions by the central bank could therefore become inaccurate.

If for example the economic outlook is getting better, the central bank might be inclined to tighten it's policy in an anticipation of higher inflation as a consequence of higher credit extensions. But since the stock is highly correlated with economic activity due to revaluations and write-downs, which are by itself highly dependent on the performance of the economy, credit trends might be overstated. In such a case, new lending might not react as vividly to the better economic outlook as the stock. This then overstates the effects on future economic activity, as upward revaluations in the stock should have a negligible impact on future economic activity.[15]

This overestimation, among potential other factors, might be a reason why the ECB raised policy rates in the summer of 2011 amid still falling new lending data in the Euro area. While giving high emphasis to the second pillar of the mandate, the monetary side, the ECB might have reacted too early with raising rates, and had to unwind this rise later that year. Specifically, they based a part of their decision on a strengthening growth of loans, since this underlying pace of monetary expansion (together with ample liquidity) seemed to have "the potential to accommodate price pressures in the euro area" (ECB (2011)). As Behrendt (2016) showed, new lending was still falling in the middle of 2011, albeit at a slower pace than before, and the growth of the stock was mainly due to the influences of higher upward revaluations and falling write-downs after the initial stages of the financial crisis.

The other important implication of the results is the feed-through of changes in the policy rate towards lending. While certain estimations show a negative effect of the change in the real policy rate of between -1% and -2% (see f.e. Gambacorta and Marqués-Ibáñez (2011)), this study does not find any evidence to underpin this using stock data. Surprisingly, the coefficients for the policy rate in the new lending models are in the expected vicinity of those from other studies.

[15] Clearly, the resulting better bank health would insert a positive impact on the ability to extend new loans, but there is no direct impact on real economic activity due to this, especially not in the magnitude as postulated by the rise in the stock.

Additionally, the magnitudes of most coefficients are exceedingly smaller in the stock model, than in the new lending model. While this is expected because of the high inertia due to the incorporation of previously extended loans in the outstanding stock data, it can certainly affect monetary policy decisions. Higher GDP growth of 1% would lead to an increase of new lending of around 0.4% and 0.9%, while the growth of the stock would only accelerate by around 0.2%. These two estimates probably have different feedback effects to real economic activity, and therefore to inflation dynamics. Other determinants are also suffering from this problem, as magnitudes, significances and even signs differ for certain variables.

This does not mean that the conduct of policy should change, but only that the rationale on which monetary policy decisions are based while looking at credit developments should be revised, as different determining factors are deemed crucial for credit developments while looking at new lending, rather than by only analysing stock data.

This study highlights the importance of the choice of the credit variable in the empirical estimation of determinants for bank lending. Previous studies using the outstanding stock may have under- or overestimated the impact of certain variables for credit extension, due to the disturbing factors inherent in the stock. This paper therefore specifically applies data for new lending to better capture the rationale for credit supply and demand.

6 Appendix

Table 1: Data definitions and sources for the panel model

Variable	Description	Calculation Method	Expected Sign	Source
New Lending	Loans to households and non-financial coorporations - bank new business volumes (MIR framework)	mom log change		ECB
ΔStock	Loans vis-a-vis euro area MFI excluding ESCB - outstanding amounts	mom log change		ECB
Δ ΔStock	Loans vis-a-vis euro area MFI excluding ESCB - outstanding amounts	change of the mom log change		ECB
Loan Rate	Bank interest rates for new business loans (MIR) (annual agreed rate)	weighted average of the loan rate in relation to the amount of new business loans for each category	-/+	ECB
ΔGDP	Gross domestic product in mill. Euro	yoy change	+	Eurostat
Inflation	Harmonised index of consumer prices (overall index)	yoy change	+	ECB
ΔESI	Economic Sentiment Index	mom change	+	European Commission
Inflation Expectations	Price trends over next 12 months (Consumer Survey question)		+	European Commission
ΔrEONIA	change in the real EONIA rate	Inflation rate as reference value	-	ECB
CISS	Sovereign Systemic Stress Composite Indicator		-	ECB
Liquidity	Securities and cash in relation to total assets of MFIs		+	ECB
Loan Ratio	Outstanding amount of loans in relation to total assets of MFIs		-	ECB
Capital Ratio	Capital and reserves in relation to total assets of MFIs		+	ECB
BLS Demand	Bank Lending Survey question 4: change in demand for loans to enterprises - backward looking 3 months - Diffusion index		+	ECB
BLS Supply	Bank Lending Survey question 1: change in credit standards to enterprises - backward looking 3 months - Diffusion index		-	ECB

Table 2: Summary statistics for the panel model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
New Lending	352	-0.265	6.336	-21.952	19.161
ΔStock	352	0.905	1.721	-4.889	7.262
Δ ΔStock	352	-0.034	1.048	-4.034	6.319
Loan Rate	352	3.855	1.11	1.93	6.958
ΔGDP	352	1.872	2.305	-5.764	6.156
Inflation	352	1.504	0.87	-1.573	4.404
ΔESI	352	0.205	4.911	-20.027	14.086
Inflation Expectations	352	1.703	1.642	-2.84	6.213
ΔrEONIA	352	-0.028	0.484	-1.727	1.34
CISS	352	0.235	0.227	0.011	0.96
Liquidity	352	23.086	6.438	12.737	38.316
Loan Ratio	352	34.711	10.744	18.305	60.264
Capital Ratio	352	6.637	2.055	3.435	13.829
BLS Demand	352	-0.476	1.658	-6.3	3.6
BLS Supply	352	0.820	1.793	-2.5	8

Table 3: AR(1) model

	(1) dStock	(2) dStock	(3) dNew	(4) dNew	(5) ddStock	(6) ddStock
AR(1)	0.939***	0.811***				
	(14.86)	(4.99)				
Loan Rate	0.462	0.458	0.495	-0.002	0.114	0.066
	(1.28)	(1.35)	(0.45)	(-0.00)	(0.82)	(0.42)
ΔrEONIA	-0.086	-0.107	-1.244	-0.743	-0.058	-0.010
	(-0.57)	(-0.67)	(-1.08)	(-0.58)	(-0.40)	(-0.06)
ΔGDP	-0.066	-0.050	0.677*	0.532	-0.068	-0.082*
	(-0.52)	(-0.53)	(2.02)	(1.42)	(-1.63)	(-1.75)
ΔESI	-0.015	-0.020	-0.056	-0.062	0.006	0.005
	(-0.52)	(-0.58)	(-0.46)	(-0.51)	(0.37)	(0.32)
CISS	-0.057	-1.347	-7.717*	-4.338	-0.849	-0.526
	(-0.06)	(-1.22)	(-1.80)	(-0.76)	(-1.58)	(-0.73)
BLS Demand	0.622	0.599	2.911	3.186	-0.185	-0.159
	(1.09)	(1.05)	(0.90)	(0.98)	(-0.46)	(-0.39)
BLS Supply	0.264	0.856	-1.027	-0.117	-0.353	-0.266
	(0.47)	(1.04)	(-0.21)	(-0.02)	(-0.57)	(-0.42)
Break		-0.895*		-1.726		-0.165
		(-1.82)		(-0.89)		(-0.68)
Constant	-0.892	-0.131	-1.474	0.827	-0.125	0.094
	(-0.57)	(-0.09)	(-0.36)	(0.17)	(-0.25)	(0.16)
sigma						
Constant	0.302***	0.289***				
	(7.13)	(7.20)				
No. of obs	44	44	44	44	44	44

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Demand side new lending panel models

	(1) OLS	(2) FE	(3) FE	(4) IV	(5) IV	(6) IV	(7) 3SLS
Loan Rate	0.129	0.407	0.763	-0.379	-2.168	-4.062*	-1.286**
	(0.40)	(0.94)	(0.71)	(-0.45)	(-1.61)	(-1.77)	(-2.47)
ΔGDP	0.404**	0.358*	0.390	0.453**	0.671***	0.901**	0.361**
	(2.25)	(1.86)	(1.10)	(2.14)	(2.63)	(2.57)	(3.09)
Inflation	0.638	0.931*	0.530	1.020*	1.221**	1.434**	0.323
	(1.28)	(1.68)	(0.67)	(1.81)	(2.04)	(2.10)	(1.16)
ΔESI	0.225***	0.246***	0.024	0.217**	0.149	0.078	-0.000
	(2.60)	(2.82)	(0.15)	(2.36)	(1.44)	(0.59)	(0.00)
Inflation	0.142	-0.031	0.083	-0.013	0.029	0.073	0.287*
Expectations	(0.63)	(-0.10)	(0.18)	(-0.04)	(0.09)	(0.20)	(2.16)
BLS Demand	0.504**	0.556**	0.430	0.563**	0.580**	0.597**	0.656***
	(2.38)	(2.49)	(1.56)	(2.51)	(2.46)	(2.32)	(3.91)
Constant	-2.529*	-3.637**	-4.079	-0.940	5.200	11.70	3.355*
	(-1.82)	(-2.14)	(-0.77)	(-0.32)	(1.10)	(1.48)	(1.72)
F-Statistic				20.97	14.51	16.80	
Sargan-Hansen				5.442	1.543		
p-Value				0.364	0.462		

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Instruments:

(4): ΔrEONIA; CISS; Liquidity; LoanRatio; CapitalRatio; BLS Supply

(5): CISS; CapitalRatio; BLS Supply

(6): CISS

The F-Statistic depicts values for the Sanderson-Windmeijer multivariate F test of weak instruments. Values below 10 would indicate that the applied instruments are weak (see Sanderson and Windmeijer (2016)). The Sargan-Hansen test checks for overidentification. The null hypothesis is that the excluded instruments are valid, which means that they are uncorrelated with error term. A rejection would cast doubt on the validity of the instruments.

Table 5: Supply side new lending panel models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FE	FE	IV	IV	IV	3SLS
Loan Rate	1.003***	1.030**	1.311	3.536**	3.453**	4.551*	3.469***
	(2.74)	(2.13)	(1.12)	(2.39)	(2.30)	(1.72)	(3.62)
ΔrEONIA	-0.591	-0.598	0.747	-1.554*	-1.522*	-1.941	-1.550***
	(-0.84)	(-0.83)	(0.71)	(-1.70)	(-1.66)	(-1.55)	(-2.98)
CISS	-3.847*	-3.820	-4.039	-8.084**	-7.942**	-9.810*	-3.663***
	(-1.78)	(-1.57)	(-1.18)	(-2.34)	(-2.28)	(-1.92)	(-2.70)
Liquidity	-0.093	-0.092	-0.073	0.165	0.156	0.268	0.059
	(-1.42)	(-0.79)	(-0.45)	(0.88)	(0.83)	(0.92)	(1.41)
LoanRatio	-0.108**	-0.099	-0.150	-0.107	-0.107	-0.110	-0.182***
	(-2.38)	(-0.67)	(-0.92)	(-0.69)	(-0.69)	(-0.69)	(-4.03)
CapitalRatio	0.305	0.159	0.287	0.531	0.519	0.682	0.591***
	(1.44)	(0.44)	(0.62)	(1.24)	(1.21)	(1.25)	(3.48)
BLS Supply	-0.396*	-0.451*	-0.137	-0.729**	-0.720**	-0.841**	-1.010***
	(-1.72)	(-1.88)	(-0.47)	(-2.49)	(-2.45)	(-2.18)	(-4.09)
Constant	0.960	1.543	0.371	-15.05	-14.50	-21.77	-10.94**
	(0.35)	(0.27)	(0.05)	(-1.37)	(-1.30)	(-1.19)	(-2.94)
F-Statistic				8.66	10.45	13.57	
Sargan-Hansen				4.62	4.55		
p-Value				0.33	0.20		

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Instruments:

(4): ΔGDP; Inflation; ΔESI; Inflation Expectations; BLS Demand

(5): ΔGDP; Inflation; ΔESI; BLS Demand

(6): BLS Demand

The F-Statistic depicts values for the Sanderson-Windmeijer multivariate F test of weak instruments. Values below 10 would indicate that the applied instruments are weak (see Sanderson and Windmeijer (2016)). The Sargan-Hansen test checks for overidentification. The null hypothesis is that the excluded instruments are valid, which means that they are uncorrelated with error term. A rejection would cast doubt on the validity of the instruments.

Table 6: Overview of the panel stock models

Model	**Explanation**	**Drawback**
(1) OLS	Ordinary Least Sqares Estimation	Upward bias for the coefficient of the lagged dependent variable due to the unobserved heterogeneity + only exogenous variables
(2) FE	Country fixed effects estimation	Downward bias for the coefficient of the lagged dependent variable due to the correlation between the lagged dependent variable and the error term + only exogenous variables
(3) FEIV	Country fixed effects estimation using instrumental variables	Downward bias for the coefficient of the lagged dependent variable due to the correlation between the lagged dependent variable and the error term
(4) ABIV	Arrelano-Bond GMM estimation using instrumental variables	small sample bias
(5) BBIV	Blundell-Bond GMM estimation using instrumental variables	small sample bias
(6) LSDVC	Least Squares Dummy Variable Correction	only exogenous variables

Table 7: Demand side stock panel models

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	FE	FEIV	AB	BB	LSDVC
Δ $Stock_{t-1}$	0.687***	0.652***	0.682***	0.653***	0.623***	0.688***
	(17.37)	(15.60)	(11.48)	(15.16)	(17.86)	(16.24)
Loan Rate	-0.009	-0.051	-1.265***	-0.051	-0.077	-0.082
	(-0.19)	(-0.74)	(-3.22)	(-0.73)	(-1.44)	(-0.99)
ΔGDP	0.172***	0.194***	0.327***	0.193***	0.204***	0.190***
	(5.20)	(5.49)	(5.05)	(5.31)	(6.91)	(4.96)
Inflation	-0.008	-0.035	0.111	-0.036	-0.014	-0.0228
	(-0.10)	(-0.40)	(0.85)	(-0.40)	(-0.19)	(-0.24)
ΔESI	0.052***	0.052***	0.005	0.051***	0.055***	0.052***
	(3.80)	(3.75)	(0.19)	(3.61)	(4.61)	(3.71)
Inflation	-0.005	0.030	0.057	0.032	0.049	0.037
Expectations	(-0.13)	(0.62)	(0.83)	(0.62)	(1.22)	(0.70)
BLS Demand	0.069**	0.077**	0.086*	0.077**	0.090***	0.076*
	(2.01)	(2.11)	(1.69)	(2.06)	(2.79)	(1.91)
Constant	0.021	0.155	4.305***	0.158	0.206	
	(0.10)	(0.58)	(3.18)	(0.58)	(0.97)	
Observations	344	344	344	336	344	344
Hansen test of over-identification (p-value)				0.686	0.214	0.533

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Instruments in (3), (4), and (5): CISS

20 repetitions are used for the calculation of the bootstrapped variance-covariance matrix in model (6).

Table 8: Supply side stock panel models

	(1) OLS	(2) FE	(3) FEIV	(4) AB	(5) BB	(6) LSDVC
Δ $Stock_{t-1}$	0.733***	0.607***	0.528***	0.607***	0.644***	0.638***
	(20.21)	(13.90)	(7.56)	(13.82)	(18.47)	(13.51)
Loan Rate	0.068	0.033	1.193**	0.032	-0.001	0.024
	(1.13)	(0.44)	(2.04)	(0.42)	(-0.02)	(0.26)
ΔrEONIA	0.072	0.114	-0.321	0.117	0.094	0.112
	(0.64)	(1.03)	(-1.23)	(1.05)	(1.03)	(0.75)
CISS	-1.325***	-1.181***	-3.247***	-1.186***	-0.884***	-1.137**
	(-3.73)	(-3.12)	(-2.85)	(-3.09)	(-2.66)	(-2.00)
Liquidity	-0.011	-0.021	0.092	-0.020	-0.048***	-0.012
	(-0.99)	(-1.10)	(1.51)	(-1.04)	(-3.24)	(-0.48)
Loan Ratio	-0.000	-0.060**	-0.074**	-0.061**	-0.009	-0.060*
	(-0.01)	(-2.51)	(-2.28)	(-2.49)	(-0.72)	(-1.91)
Capital Ratio	0.012	-0.158***	-0.026	-0.160***	-0.061	-0.174*
	(0.34)	(-2.69)	(-0.26)	(-2.67)	(-1.35)	(-1.78)
BLS Supply	-0.024	-0.031	-0.154**	-0.030	-0.028	-0.032
	(-0.67)	(-0.84)	(-1.97)	(-0.81)	(-0.85)	(-0.62)
Constant	0.468	4.139***	-2.686	4.174***	2.357***	
	(1.06)	(4.11)	(-0.74)	(4.09)	(3.95)	
Observations	344	344	344	336	344	344
Hansen test of over-identification (p-value)				0.495	0.038	0.554

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Instruments in (3), (4), and (5): BLS Demand

20 repetitions are used for the calculation of the bootstrapped variance-covariance matrix in model (6).

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