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Informing macroprudential policy choices using credit supply and demand decompositions

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Abstract

Macroprudential policies should strengthen the banking sector throughout the financial cycle. However, while bank credit growth is used to capture cyclical exuberance and calibrate buffer requirements, it depends on potentially heterogeneous dynamics on the borrower and lender sides. By decomposing credit growth into a common component and components capturing heterogeneity in supply and demand *à la* Amiti and Weinstein, 2018 applied on the euro area credit register ("AnaCredit"), we can inform the policy debates in two ways. *Ex ante*, we introduce a framework mapping the decomposition to different types of macroprudential instruments, specifically broad vs targeted measures. *Ex post*, we also show that the resulting decomposition can be used to assess the effectiveness of adopted measures on credit supply or demand. We find evidence that buffer releases and credit guarantees increased bank credit supply during the COVID-19 pandemic and interacted positively with banks' profitability.

Keywords: Capital requirements; Buffer Releases; European Economy; Bank-lending channel; Credit Dynamics

JEL Classification: E58, E52, E44, G21

Non-technical summary

Macroprudential policies encompass various tools to prevent the excessive build-up of systemic risk and smooth the adverse effects of a crisis. Suppose, for instance, to observe excessive corporate credit growth: should the policymaker intervene with broad or targeted measures? In this paper, we separate credit growth into three components: a common component that captures the median credit growth across the individual bank and firm (sector) and two idiosyncratic demand and supply components that measure how heterogeneous and skewed the credit growth distribution is across borrowers and lenders. We build on Amiti and Weinstein (2018) and provide a framework to support policy makers in choosing among different macroprudential tools.

The insight we propose is the following: a significant common component indicates that most banks and firms lend and borrow at a high rate. If this is the case, broad-based policy measures should be appropriate (e.g. countercyclical capital buffer, systemic risk buffer). Alternatively, a significant bank supply component indicates that a subset of banks generates a materially higher credit growth than the rest of the banking system, suggesting bank-targeted measures are more appropriate (e.g. P2G, P2R). Finally, a significant borrower component (driven by granular firms or firms belonging to a specific sector) would call for sectoral buffers or the introduction of measures limiting extensive exposure (e.g. sectoral countercyclical capital buffer).

To estimate the three credit growth components, we rely on the methodology proposed by Amiti and Weinstein (2018), using more than 82 million bank-firm observation pairs from AnaCredit. We advance the AW methodology by complementing it with the clustering strategy of Degryse et al. (2019) to include single-bank firms in the estimation and with the mid-point growth rate definition used by Beaumont et al. (2019) to better deal with the problems created by the entry and exit of firms in our dataset.

In addition, we demonstrate that the resulting indicators are meaningful in an economic sense as we apply the components to study one macroprudentially relevant issue. We investigate the impact of capital buffer releases on banks' lending behaviour during the Covid-19 pandemic and find that they increased banks' idiosyncratic credit supply. The effect of the capital releases on bank credit supply is more extensive for more profitable banks.

1 Introduction

Macroprudential policies encompass various tools to prevent the excessive build-up of systemic risk and smooth the adverse effects of a crisis. However, policy tools are heterogeneous and fragmented, including country-, sectoral- or bank-specific measures, prescribing - minimum capital, liquidity, or concentration requirements. As such, the choice of which tool to employ is not apparent.

Suppose, for instance, to observe excessive corporate credit growth: should the policymaker intervene with broad measures which penalise all exposures, with targeted measures on some banks, with targeted measures on a set of firms or a combination of the above? The policy choice depends on the underlying drivers of credit growth: whether it is broad-based or whether some banks (firms) are lending (borrowing) quickly. By informing the lively debate on the correct macroprudential policy action,[1] we contend that this policy choice can be meaningfully informed by two considerations: (i) whether credit growth is driven by a common component (e.g. which is the case when the median level of credit growth across lenders or borrowers is high); and/or, (ii) whether credit supply (demand) is heterogeneous across banks (firms).

In this paper, we separate credit growth into three components: a common component which captures the median credit growth across individual banks/firms and idiosyncratic demand and supply components which measure how heterogeneous and skewed the credit growth distribution is across borrowers and lenders. We build on Amiti and Weinstein (2018) and provide a framework to support policy makers in choosing among possible tools. While a sizeable common component indicates that credit grows fast for most firms and banks, the aggregated idiosyncratic supply and demand components inform on the behaviour of the tails of the bank and firm distributions. A significant positive (negative) demand component indicates that a subset of firms experiences rapid credit expansion (contraction). The approach allows us to identify whether a group of granular banks or firms (sectors) is driving the change in credit and suggest the most appropriate policy instrument.

To estimate the three components, we rely on the methodology proposed by Amiti and Weinstein (2018) ("AW" in the rest of the paper). In addition to the use of firm-time fixed effects made popular by Khwaja and Mian (2008), the AW estimation produces components that match aggregated data, i.e. their weighted average matches exactly the growth rates computed

[1] See e.g. Wildmann and Pirovano (2019); Castro (2019); Cantone et al. (2019); Galaasen and Solheim (2018); Fiori and Pacella (2019); European Systemic Risk Board (2016, 2021)

at bank, firm, and economy-wide levels. We advance the AW methodology by complementing it with a firm-clustering strategy as in Degryse et al. (2019) to include single-bank firms in the estimation and with the mid-point growth rate definition used by Beaumont et al. (2019) to better deal with the problems created by the entry and exit of firms in our dataset.

In addition to showing how the aggregate decomposition informs *ex ante* macroprudential policy choices, we demonstrate that the resulting granular indicators help assess *ex post* the effectiveness of macroprudential measures. For example, we investigate the impact of capital buffer releases on banks' lending behaviour during the Covid-19 pandemic and find that they increased the idiosyncratic credit supply of the largest euro area banks.[2] We also show that the positive effect of releases on banks' lending behaviour increases with their profitability, hinting at concerns by banks over buffer replenishment paths.

Advances in the study of supply and demand developments on a cross-country basis have been made empirically possible by the recent increase in available loan-level data. For this purpose, we analyse novel and confidential loan-level data from "AnaCredit", the Eurosystem register of financial instruments granted by banks to non-financial corporations (NFC). AnaCredit contains bank and firm-level information based on unique entity identifiers starting in September 2018. As a result, our estimations include up to 82 million bank-firm observation pairs.

Our work relates to the literature on macroprudential tools, which suggests that targeted measures can effectively complement broad-based tools in the macroprudential toolkit (Galaasen and Solheim, 2018; Wildmann and Pirovano, 2019; Cantone et al., 2019; Fiori and Pacella, 2019; Castro, 2019). As this debate is largely based on theoretical models, we advance its findings by informing the choice between broad vs narrow buffers through extensive empirical analysis. We complement the large literature assessing the impact of capital buffer requirements (Fonseca et al. (2010); Drehmann and Gambacorta (2012); Coffinet et al. (2012); Jiménez et al. (2017); Berrospide and Edge (2019); Berrospide et al. (2021))[3] by not looking at the *ex-post* impact of the policies, but by taking a step back and informing the policy maker *ex-ante* on which policies would be most appropriate to address a given risk.

[2]In our sample, these include the Significant Institutions (SI) under the direct supervision of the Single Supervisory Mechanism (SSM)

[3]By studying the impact of buffer releases on the bank idiosyncratic component during the Covid-19 pandemic, we also speak to the literature on the bank-lending channel of monetary policy transmission (Bernanke and Gertler, 1989, 1995). Past studies estimate the impact of bank shocks on loan supply using natural experiments (Peek and Rosengren, 1997, 2000; Paravisini, 2008), bank-level data (Kashyap and Stein, 2000), or survey data (Altavilla et al., 2018). Results based on loan-level data include Gan (2007); Khwaja and Mian (2008); Jiménez et al. (2012); Bottero et al. (2015); Alfaro et al. (2021); Beaumont et al. (2019)

We also speak to the growing number of studies investigating credit developments and policies' effects during the Covid-19 pandemic. Finally, we are among the first to empirically estimate the impact of buffer releases on bank supply during the Covid-19 pandemic in Europe (for a theoretical discussion, see, e.g. Borsuk et al. (2020)). Analysing different data sources, (Altavilla et al., 2020a) found a positive impact of the monetary, microprudential, and macroprudential policies implemented during the pandemic. The authors also note that there was an essential complementarity between buffer releases and monetary policy easing during the pandemic, i.e. TLTROs. Using a large-scale semi-structural model, the results are also confirmed in (Budnik et al., 2021). In line with Couaillier et al. (2021a), who focus on the differential lending response of banks with different capital headrooms, we use AnaCredit data and exploit its unique granularity. Differently from these authors, we first disentangle demand from supply and then test the effect of the policies. Next, we also provide evidence that credit guarantees had a positive impact on bank supply during the Covid-19 pandemic, similar to initial results found in Granja et al. (2020) for the USA, and Kozeniauskas et al. (2020); Core and De Marco (2021); Gourinchas et al. (2021); Altavilla et al. (2021) for Europe.[4]

Finally, most studies that employ bank-borrower data largely focus on a single country setting, and therefore their results may have limited applications to other jurisdictions (Paravisini et al., 2015; Amiti and Weinstein, 2018; Alfaro et al., 2021; Fraisse et al., 2020; Greenstone et al., 2020; Berton et al., 2018; Amador and Nagengast, 2016; Manaresi and Pierri, 2018; Beaumont et al., 2019).[5] By employing a comprehensive and unique European dataset such as AnaCredit, our analytical framework is applied in a multi-country setting, increasing the cross-country validity of our findings.

The rest of the paper is organized as follows. Section 2 discusses the decomposition methodology while Section 3 describes the AnaCredit data used. Section 4 introduces the macroprudential policy choice framework and Section 5 applies it to a subset of euro area countries. Section 6 shows how the decomposition can be used to shed light on macroprudential relevant issues, namely on the impact of capital releases. Finally, Section 7 concludes the paper.

[4]Studies already available on policies during the pandemic include also a comparison of the effects of transfers vis-á-vis credit subsidies (Bigio et al., 2020); observations on the expected restructuring of the corporate sector (Greenwood et al., 2020); and considerations on the impact on public finances (Hanson et al., 2020).

[5]Notable exceptions of multi-country studies are Altavilla et al. (2020b) and Altavilla et al. (2021) For studies estimating supply with firm-time fixed effects to control for demand, see Paravisini (2008); Chodorow-Reich (2014); Jiménez et al. (2014, 2017); Behn et al. (2016); Carletti et al. (2021).

2 Methodology

Amiti and Weinstein (2018)'s seminal contribution introduced a method to identify bank supply components exploiting matched bank-firm credit data. First, it regresses bank-firm credit growth on a complete set of bank-time and firm-time fixed effects. It then defines a "common component" as the median fixed effect across all banks and firm fixed effects in a given period. Finally, it represents as "demand" (supply) component the de-medianed firm and bank-level fixed effects for the same period. A key feature of AW decomposition is that the sum of the contributions equals the aggregate credit growth.[6] This perfect transition between micro and macro levels is very convenient from a policy perspective to identify the materially of financial risks and thus design the appropriate prudential tool. The AW method also accounts for the impact of new lending relationships and produces bank components without relying on any instrumental variable estimation.

However, an essential condition in AW's approach is the presence of multiple firm lending relationships, which is not always a feature of our data. To include single-bank firms in the estimation, we cluster firms by country and industry (NACE 2) following Degryse et al. (2019).[7] An essential assumption behind using clusters in the AW estimation is that firms within the same cluster have a similar demand for credit. We argue that this assumption is reasonable in our case and that the industry clusters suit a macroprudential analysis for which tools are available at the sectoral level. Moreover, the sectoral aggregation allows for precise identification of sector-specific credit momentum, thus informing the policymakers regarding the appropriateness of sector-specific measures, which constitute the vast majority of borrower-targeted measures.[8] All in all, entities at this level of consolidation are rarely specialized in lending towards a specific industry.[9] Alternatively, we aggregate firms at their NACE-2 sector level, running the credit

[6]Their method adopts weighted least squares and normalizes the coefficients to the median bank and the median firm component (see also Tielens and Van Hove, 2017). AW prove that by using linear growth rates (instead of, e.g. the log-difference specification) and the loans in $t-1$ as weights, their method produces estimators that can be consistently aggregated and match the loan growth rate in $t-1$ at bank, firm, and economy-wide level.

[7]AW's methodology is flexible and allows the use of different types of clusters in its estimation. The paper adopts the industry cluster as a baseline since macroprudential instruments are mostly sector-based. Therefore, the analysis in Appendix E is based on an industry-location cluster for single-bank firms. This more granular clustering approach allows estimating demand components at the more granular individual firm level, thus enabling matching with ORBIS firm-level balance sheet data.

[8]Following Degryse et al. (2019), we also check our results using industry-location-time clustering, where location is derived by the postal codes of the firms at the regional level. The alternative clustering does not change our results. We maintain the industry-country-time clustering to ease our policy interpretation at the sectoral or country level.

[9]For more detail, see AnaCredit Reporting Manual - Part 1 (p. 17ff), available at `https://www.ecb.europa.eu/pub/pdf/other/AnaCredit_Manual_Part_I_General_Methodology_201905~e4b471a87e.en.pdf`,

growth decomposition at the bank-sector level. The common component accounts for the median growth rate across banks and sectors. The demand component informs on the heterogeneity of credit growth across industries, thus directly informing the appropriateness of sector-based targeted measures.

In addition to Amiti and Weinstein (2018), we adopt mid-point growth rates as in Beaumont et al. (2019) so that, controlling to the standard growth rate, new and extinguishing lending relationships can be included in the estimation. Mid-point growth rates $D(L_{fbt}/L_{fb,t-1})$ are defined as:

$$D(L_{fbct}/L_{fbc,t-1}) = 2 * \frac{L_{fbct} - L_{fbc,t-1}}{L_{fbct} + L_{fbc,t-1}} \tag{1}$$

where $L_{fbc,t}$ is the loan at time time t from bank b in country c to firm-cluster f (the baseline cluster is by country and industry). As such, a new credit relation ($L_{fbc,t-1} = 0$) results in a mid-point growth rate of 2 and a termination credit relation ($L_{fbc,t} = 0$) of -2. The advantage of using mid-point growth rates is twofold. First, contrary to the standard growth rate, it takes a finite value when the initial credit volume is zero. We can therefore consider both "entry and exit" of loans in our estimation.[10] Second, mid-point growth rates are bounded in the interval $[-2, 2]$. Since the granularity of the data can exacerbate outlier growth rates, the mid-point growth rates help mitigate the impact of extreme observations. The resulting AW decomposition returns components are also measured in mid-point growth rates.[11]

In line with the AW approach, our estimation amounts to:

$$D(L_{fbct}/L_{fbc,t-1}) = \alpha_{fct} + \beta_{bct} + \epsilon_{fbct} \tag{2}$$

where $D(L_{fbct}/L_{fbc,t-1})$ is the year-to-year mid-point growth rate defined as in Eq. 1; L_{fbct}

[10]Notice that mid-point growth rates measure entry and exit symmetrically, while linear growth rates do not. For example, a loan increasing from 0 to 10 has an infinite linear growth rate and mid-point growth rate equal to 2. A loan decreasing from 10 to 0 has a linear growth rate of -1 and a mid-point growth rate of -2. If the loan increased from 1 to 10 and decreased from 10 to 1, their mid-point growth rate would be 1.64 and -1.64, respectively. The equivalent linear growth rates would be 900% and -90%, respectively.

[11]Notice that linear growth rates and mid-point growth rates do not differ excessively in the interval $[-1, 1]$ (See Fig. A.1). The main difference between the two measures is in the tails: linear growth rates are low-bounded at -1 and have no upper bound. In contrast, mid-point growth rates are more similar to a logarithm, approaching the lower bound faster and the upper bound slower than a linear growth rate. In our analysis, the sign and the relative contribution of the components do not differ substantially between the two methods. The mid-point growth rates, however, provide aggregated growth rates that are more comparable with the Balance Sheet Items (BSI) Data (See Fig. 1). We conclude that the entry and exit of loan relationships and the limitation of the potentially "unbounded" upper bias of linear growth rates play an essential role in our data and are well accounted for using the mid-point method.

is the loan from bank b in country c to firm f at time t; α_{fct} is the vector of $f \in (1,..,F)$ firms fixed effects and β_{bct} is the vector of $b \in (1,..,B)$ banks fixed effects for country c at time t.[12]

The coefficients α_{fct} and β_{bct} are initially normalized to an arbitrary firm and an arbitrary bank. Following Amiti and Weinstein (2018), we re-normalize the coefficients regarding the median component in the following way:

$$D(L_{fbct}/L_{fbc,t-1}) = \widetilde{\alpha}_{fct} + \widetilde{\beta}_{bct} + (\overline{\alpha}_{ct} + \overline{\beta}_{ct}) \tag{3}$$

where $\widetilde{\alpha}_{fct} = \alpha_{fct} - \overline{\alpha}_{ct}$ is the firm-cluster specific idiosyncratic demand component in respect of the median firm component $\overline{\alpha}_{ct}$ in country c at time t; $\widetilde{\beta}_{bct} = \beta_{bct} - \overline{\beta}_{ct}$ is the bank-specific idiosyncratic supply component with reference to the median bank component $\overline{\beta}_{ct}$ in country c at time t; and $(\overline{\alpha}_{ct} + \overline{\beta}_{ct})$ is defined as the "common" component.

For the aggregate analysis, loan-specific coefficients can then be aggregated into country components for each time t as follows:

$$\sum_{fbc\,\in\,G_t} D(L_{fbct}/L_{fbc,t-1}) w_{fbct} = \underbrace{\sum_{fbc\,\in\,G_t} \widetilde{\alpha}_{fct} w_{fbct}}_{\equiv\,\alpha_{ct}} + \underbrace{\sum_{fbc\,\in\,G_t} \widetilde{\beta}_{bct} w_{fbct}}_{\equiv\,\beta_{ct}} + (\overline{\alpha}_{ct} + \overline{\beta}_{ct}) \tag{4}$$

Where G_t is the set of fb pairs in country c in which $D(L_{fbct}/L_{fbc,t-1})$ is well defined[13], and mid-point weights are defined as:

$$w_{fbct} = \frac{L_{fbct} + L_{fbc,t-1}}{\sum_{fbc} L_{fbct} + \sum_{fbc} L_{fbc,t-1}} \tag{5}$$

As such, an aggregate α_{ct} component close to (away from) zero means that the weighted firm-cluster specific $alpha_{fct}$ sum is close to (away from) zero, implying their distribution is quite (a)symmetric. The same reasoning applies to β_{ct}.

In the applications that follow, Section 4 shows how Eq. 4 is used as a macroprudential policy tool, while the results of Eq. 3 are validated in Section 6.

[12]For the details of the AW estimation procedure via weighted least squares, we remind to Amiti and Weinstein (2018), especially Appendix B, C, and D, and to Tielens and Van Hove (2017).

[13]Notice that by a different definition of G_t, loan-specific components can be aggregated also for different dimensions, such as bank, firm, or industry level.

3 Data

The credit growth decomposition is based on AnaCredit,[14] the Eurosystem's "Analytical Credit Database", which covers a reporting population of around 3000 individual Euro area banks and around 26 million credit instruments for 4.5 million debtors.[15] Data are reported monthly starting in September 2018.[16] Information on the borrower is obtained via the ECB's Register of Institutions and Affiliates Database (RIAD), which includes information on the structure and legal ownership of financial and non-financial entities. To study the determinants of bank supply (Section 6.1), we merge credit register data with bank supervisory data.

As a benchmark, we compare the volume of data extracted and cleaned from AnaCredit with the Balance Sheet Item (BSI) statistics. While AnaCredit data is subject to a reporting threshold (only includes information on loans above 25.000 euros), the BSI's coverage is broader.[17] In addition to the outstanding loan amounts included in BSI statistics, our analysis encompasses off-balance sheet amounts, in line with Albertazzi and Bottero (2014), as they jointly account for the credit that is made available to firms.[18] The AnaCredit total outstanding amount alone accounts for around 82% of the BSI amount on average across countries in, e.g. June 2020, while the sum of outstanding and off-balance sheet amount almost matches the same BSI amount (Figure 1).

We compute yearly mid-point growth rates of credit for each bank-borrower relationship from January 2019 to January 2021 and include twelve Euro area countries in our study.[19] In

[14]In 2011, the ECB launched the "AnaCredit" project to collect information on individual loans in a single harmonised database. The data collection started in September 2018 and included details for all loans above 25.000 euros granted in the Euro area to a legal entity. AnaCredit does not include data on households. Also, self-employed do not qualify as legal entities and are excluded. The 25.000 euro threshold is computed for the consolidated position of the debtor at each bank level. This means that also different instruments existing between a bank and the same borrower that are individually below the threshold are nonetheless included in the database if their sum meets the threshold.

[15]The smallest unit of record in AnaCredit is the instrument level (e.g. a line of credit or a term loan). A contract can include one or more instruments.

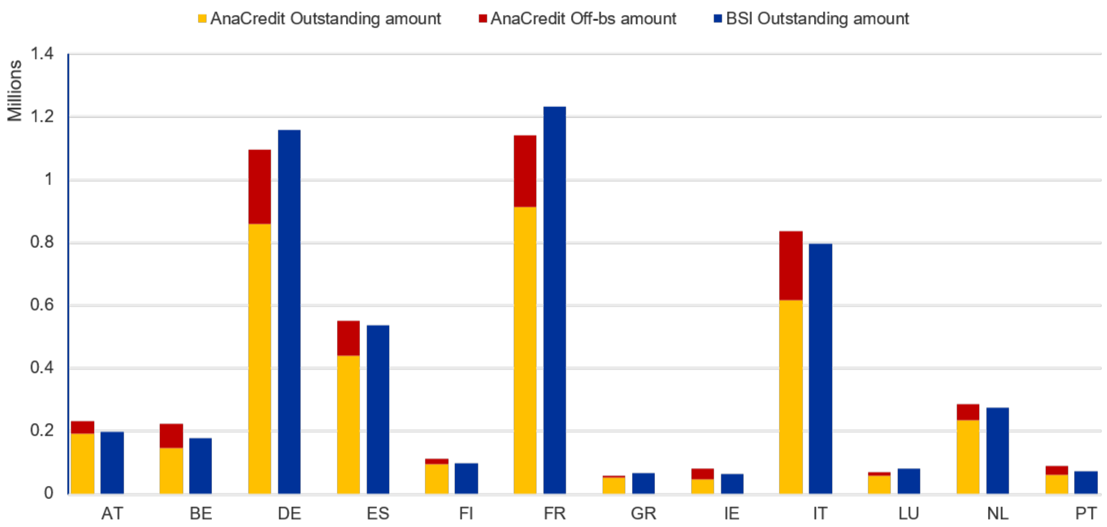
[16]Loan information reported by banks has more than 80 attributes, such as amounts, contractual dates, interest rates, and protection providers.

[17]However, BSI lacks any granular details on the lender-borrower pairs and thus cannot be used for the credit growth decomposition presented in this paper.

[18]"The outstanding nominal amount is the amount drawn under the instrument; the off-balance-sheet amount is the amount that can be potentially drawn so that the credit limit is not exceeded", AnaCredit Reporting Manual - Part 1 (p. 49), available at `https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html`

[19]We start using data from January 2019 as data for the year 2018 are only partially reported due to the transition period granted to banks to start reporting in AnaCredit. We include Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, and Portugal.

Figure 1: Comparison of amounts between BSI and AnaCredit in June 2020



Source: ECB (Anacredit, BSI), authors' calculation.
Note: Data of 2020 q2. Labels indicate the ratio between the AnaCredit outstanding amount and the AnaCredit outstanding and off-balance sheet amount relatively to the BSI outstanding amount.

the estimation, we account for important mergers and acquisitions.[20] Summary statistics on the resulting dataset are presented in Table A.1. The number of firms entering our decomposition ranges between 333,262 in Italy and 2,369 in Luxembourg, with the largest number of loans recorded per month for Italy and the smallest for Luxembourg. Most banks are in Germany (956), while the fewest in Greece (36).

4 A framework to inform macroprudential policy choices

4.1 A short primer on macroprudential policy in Europe

Macroprudential policy gained traction after the 2008 financial crisis and includes procedures that aim to limit the build-up of systemic risk and increase the financial system's resilience. Measures vary across jurisdictions and are generally divided into capital-based measures, liquidity-based measures, and asset-side instruments (for an overview see e.g. Bank for International Settlements, 2010; Financial Stability Board, 2011; Aikman et al., 2013; Jayaram and Gadanecz,

[20] If two banks merge, we treat them as one bank from the beginning of the sample and sum their credit amounts by the borrower. The major merger in our sample period is between Intesa and UBI in Italy, e.g. treated as Intesa from the beginning of the sample period.

2016). In Europe, macroprudential policies are promoted and implemented by the ECB, the European Systemic Risk Board (ESRB), and national authorities.[21] The current macroprudential toolkit is varied, and the implementation of policies in the European space is highly articulated.

In the European framework, different capital requirements are envisaged to address broad and targeted sources of risk. The countercyclical capital buffer (CCyB) is a time-varying requirement for all risk-weighted assets.[22] More recently, discussions have started on the merits of a sectoral countercyclical capital buffer (SCCyB) both in international and European fora (see, e.g. Basel Committee on Banking Supervision, 2019; Wildmann and Pirovano, 2019).[23] Macroprudential authorities can also activate the systemic risk buffer (SyRB). Such a capital requirement is a highly flexible capital buffer, which authorities can tailor on banks' exposure, typically only domestic vulnerabilities or exposures to some sector (e.g. residential real estate). The SyRB can be used both as a broad based-instrument or a targeted bank-level instrument or an instrument penalising banks for targeted borrower-level exposures. Finally, European supervisors set the Pillar 2 Requirements (P2R) and the Pillar 2 Guidance (P2G), defined at the bank level to cover the individual risk.[24] As such, they can be considered targeted bank-level capital tools.

Besides capital requirements, national authorities can implement borrower-based measures. Those measures restrict borrowers' credit risk, for instance, through limits on their credit maturity or their debt-service-to-income ratio, i.e. the share of their income used to repay their debt. These measures are not defined in the common European macroprudential framework and can be set by national macroprudential authorities. Alternatively, authorities can increase (or put floors on) risk weights to increase capital requirements attached to a particular type of exposure (typically residential real estate exposures).

Finally, authorities can adopt more flexible measures, such as limits on significant exposures or minimum levels of liquid assets. Those can be adopted either by macroprudential authorities on all or a subset of banks,[25] or by supervisors at the bank-level as part of the P2R and P2G

[21] See, e.g. "The ESRB handbook on operationalising macroprudential policy in the banking sector" available at `https://www.esrb.europa.eu/pub/pdf/other/esrb.handbook_mp180115.en.pdf` (consulted on the 7th of March 2022). The report offers a detailed view of the macroprudential instruments available and the relevant institutional background. It also discusses principles of instrument selection and communication.

[22] The CCyB is set at the country level every quarter, at the country level, to increase banks' resilience against the risk of losses due to excessive credit growth. Banks then compute a bank-specific CCyB rate as the average of national rates, weighted by the bank's relevant exposure to each country.

[23] Note that the present debate also builds on past experiences, such as the case of the sectoral capital buffers implemented by the Swiss National Bank from February 2013 to March 2020.

[24] While the P2R is a requirement that banks must meet at all times, the P2G is a guide whose breach triggers no automatic intervention from the supervisors

[25] Through the activation of Article 458 of the Capital Requirement Recommendation

measures.

As such, prudential authorities are equipped with a vast range of tools to improve financial stability, both at the broad and targeted level. The variety of available tools raises the question of the optimal policy mix between those instruments.

4.2 Policy choice and trade-offs

How to choose between different types of measures? Imagine an excessive corporate credit growth episode: should the policymaker intervene with a broad (across-the-board) buffer penalising all exposures or a targeted sectoral buffer? The answer to this question depends on whether credit growth is broad-based or whether a sector (some banks or some firms) is borrowing credit quickly. If risks were confined to a specific sector (Wildmann and Pirovano, 2019) or if shifting capital across sectors were costly (Galaasen and Solheim, 2018), would a targeted tool like the SCCyB be the efficient choice?[26] Instead, if sectoral cycles were not synchronized, would a sectoral CCyB be more appropriate (see, e.g. Fiori and Pacella, 2019)?[27]

Decomposing credit growth can inform these questions and support policy-makers in their choices. For example, a large common component indicates that the median credit growth across banks and borrowers is high: most banks and borrowers experience rapid credit growth. Then, broad-based policy measures should be considered most suited (e.g. CCyB, SyRB). Alternatively, a large bank supply component indicates that a subset of banks experience materially higher credit growth than the rest of the banking system, suggesting that more bank-targeted measures are appropriate (e.g. P2G, P2R). A large borrower component (from granular firms or firms belonging to a specific sector) would call for sectoral requirements or the application of large exposure limits (e.g. SCCyB). [28]

As such, Table 1 proposes a conceptual mapping between the credit growth decomposition and possible policy recommendations. Substantial median credit growth across banks and firms points toward broad-based measures, while targeted measures can better tackle asymmetries in credit dynamics. Notably, the decomposition can simultaneously return high common and

[26] Sectoral credit can be, however, dispersed across countries, so that cross-border recognition of instruments is needed (Cantone et al., 2019).

[27] Theoretical modelling generally suggests that a SCCyB can effectively complement a CCyB, however, at a practical level, more tools require more frequent policy adjustments when simultaneously in place (Castro, 2019).

[28] For a specific study on "granular borrowers", see Beaumont et al. (2019). In general, notice that the advantage of using the components for policy purposes instead of the broad, sectoral, or bank-specific credit growth rates is that we can distinguish for each level of credit growth rates the shares determined by a common behaviour or that of idiosyncratic banks and firms.

idiosyncratic supply or demand components, thus suggesting that a mix of broad and targeted policy interventions may be better suited to taming excessive credit dynamics. Finally, the table looks at each component separately (rows) and, having assessed its strength and distributional properties, suggests a good policy course.

Table 1: Macroprudential policy choice matrix

	Size and direction of the three components		
	Highly positive	**Contained**	**Highly negative**
Common	Excessive broad-based expansion *Broad tightening measures*	Sustainable broad-based growth *No measures*	Broad-based contraction *(Release broad measures)*
Supply	Some excessive bank-level expansion *Bank-level tightening measures*	No bank-level asymmetries *No measures*	Some bank-level contraction *(Release bank-level measures)*
Demand	Some excessive sectoral expansion *Sectoral tightening measures*	No sectoral asymmetries *No measures*	Some sectoral contraction *(Release sectoral measures)*

5 Credit growth decomposition in the euro area

We decompose credit growth for 12 euro area countries from January 2020 to July 2021. Our results (presented for a selection of countries in Figure 2, left column)[29] show how different the underlying credit drivers are across jurisdictions. The common component is positive in most countries, suggesting broad-based credit growth. However, idiosyncratic components also play a large role in some countries: in Germany, the idiosyncratic bank components are materially contractionary.

In the middle and right columns of Figure 2 we explore the shape of the distribution of the two idiosyncratic components.[30] We plot the sorted cumulative sum of banks' (sectors') weighted components.[31] Since the aggregate supply (demand) component is the sum of individual bank (borrower) weighted components, a positive (negative) aggregate component implies that the distribution of these weighted individual component is tilted on the positive (negative) side. As expected, a positive (negative) supply component is associated with a fatter right (left) tail of the distribution, typically having more observations taking larger positive values. On the contrary, a balanced distribution is associated with a very small aggregate component (approaching zero).

[29] See Appendix C for the decomposition of all countries.

[30] All other countries are shown in Figures C.1-C.2.

[31] Notice that since we apply mid-point growth rates, the weights are defined as $w_{fbct} = \frac{L_{fbct}+L_{fbc,t-1}}{\sum_{fb} L_{fbct}+\sum_{fb} L_{fbc,t-1}}$

The aggregate decomposition correctly summarises the information contained in the disaggregated distribution of individual components. When it is small, the underlying distribution will be homogeneous; when it is large, it will have fat tails. In line with Table 1, it informs the policymaker on (i) the median level of credit growth, and thus the appropriateness of broad-based measures, and (ii) the presence of fat tails in the distribution of banks' or firms' idiosyncratic components.[32] This knowledge sheds some light on the appropriate choice between broad vs targeted measures.

6 Applications to macroprudential policy evaluation and surveillance

While Section 5 illustrates how our credit decomposition can inform *ex ante* the policymaker in recommending appropriate policy measures, this Section uses the decomposition to investigate *ex post* the effectiveness of macroprudential measures. Our application looks at the impact on credit supply of the capital requirement releases announced at the outbreak of the Covid-19 pandemic. Once the idiosyncratic supply and demand components have been identified, the decomposition allows for a clean assessment of their drivers and the impact of the policy measures.[33]

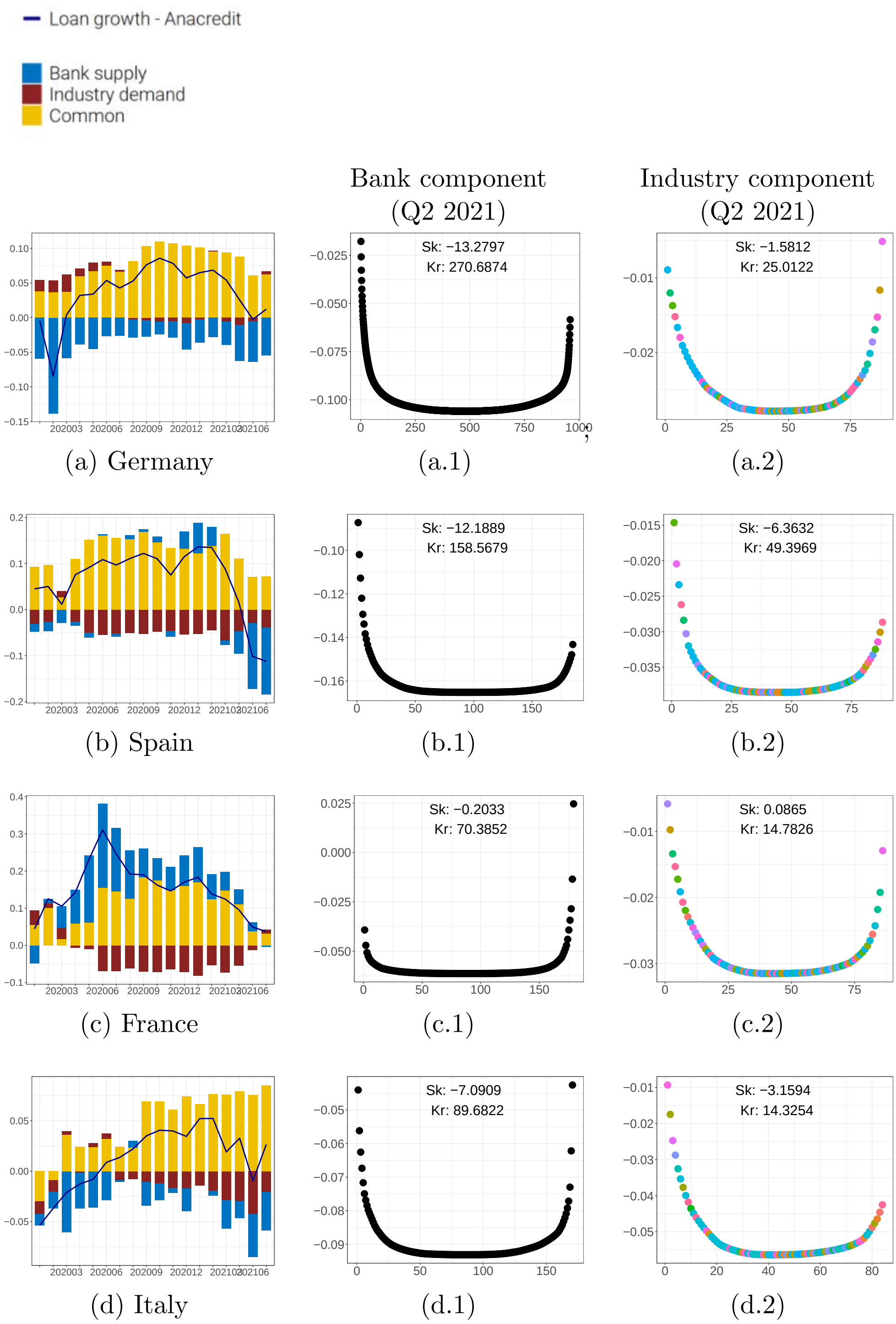
6.1 Bank credit supply determinants: the role of pandemic support policies

When faced with the Covid-19 pandemic and its vast economic shock, European and national authorities adopted various measures to reduce banks' capital requirements to simultaneously absorb losses and provide much-needed credit to a firm without breaching requirements. These measures mainly consisted of (i) reducing the combined buffer requirements (CBR) by releasing most of the CCyB and reducing some SyRB buffers and (ii) frontloading changes in the composition rules of the P2R, allowing banks to meet it partially with Additional Tier 1 and Tier

[32] Notice that entry and exit of loan relationships account for a share of the aggregate components, but not necessarily dominate its sign and value. In the case of bank-specific policy considerations, our decomposition allows to (i) to identify specific banks, such that entering or exiting banks can be recognized and evaluated for intervention or not, and (ii) distinguish for the aggregate components the shares determined by entry, exit, or existing loan relationships. This additional information enables quantifying the contributions of entry, exit, and existing components to the shape of the tails.

[33] We additionally validate the demand and supply components by showing that their relationship with loan interest rates aligns with standard theories of loan pricing (Appendix D). A complementary application (Appendix E) concerns the determinants of credit demand and their possible changes during the pandemic.

Figure 2: Credit growth decomposition and distribution of the idiosyncratic components



Note: Charts on the left-hand column show the decomposition of credit growth into common, supply, and industry component and uses industry clusters for firms (years on the x-axis, value on the y-axis). The central column shows the sorted cumulative sum of the weighted supply components in Q2 2021 (bank index on the x-axis, value on the y-axis). The right-hand column shows the sorted cumulative sum of the weighted industry component in Q2 2021, colored by sector (industry index on the x-axis, value on the y-axis).

2 capital,[34] instead of 100% CET1 as it was the case until then; any shortfall in AT1/T2 must still be met with CET1. To evaluate the effects of March 2020 releases announced by macroprudential authorities (European Central Bank, 2020a,b,c) on banks' idiosyncratic supply, we merge our data with quarterly supervisory data for a sub-sample of 286 banks, 81 of which being significant institutions.[35] We measure the intensity of buffer releases following Couaillier et al. (2021b) as:

$$
\begin{aligned}
Caprel &= \Delta cbr + \Delta p2r^{cet1} && (6)\\
&= (CCyB_{Jun20} - CCyB_{Dec19}) + \\
&\quad max(OSII_{Jun20}, GSII_{Jun20}, SRB_{Jun20}) - max(OSII_{Jun20}, GSII_{Jun20}, SRB_{Dec19}) + \\
&\quad [P2R^{cet1}_{Jun20} + shortfall^{P2R,\, at1\; t2}_{Jun20} - P2R_{Jun20}] && (7)
\end{aligned}
$$

where cbr is the combined buffer requirement; $p2r^{cet1}$ is the share of the P2R buffer that must be met with $cet1$ capital; and $shortfall^{P2R,\, at1\; t2}$ is part of the P2R that a bank could theoretically meet with AT1 or T2 but cannot due to insufficient AT1/T2, forcing the bank to meet it with CET1. The variable $Caprel$ is negatively defined and should have a negative correlation with bank supply, i.e. a deeper release of buffers are expected to have a positive effect on bank supply. We specify our model as follows:

$$
\begin{aligned}
&\widetilde{\beta}_{bc,\,post} - \widetilde{\beta}_{bc,\,pre} = \\
&\qquad \lambda_0 + \lambda_1 * Caprel_{bc} + \lambda_2 * Credit\ guarantees_{bc,\,post} + \lambda_3 * X_{bc,\,pre} + \epsilon_{bc,\,pre} \qquad (8)
\end{aligned}
$$

where $\widetilde{\beta}_{bct}$ is the bank supply component for bank b in country c; $Caprel_{bc}$ is our variable for the intensity of capital release; $Credit\ guarantees_{bc,\,post}$ is the ratio of credit guaranteed by government schemes and total assets; $X_{bc,\,pre}$ is a set of bank-level controls.[36] Since our

[34] At most 25% of T2 and 18.75% of AT1

[35] The sub-sample consists of banks for which supervisory data are complete and accurate. In the 19 countries of the monetary union, AnaCredit flags 115 important systemic institutions (SI) for around 24 trillion euros. In the 12 countries selected for this study, we have 96 SI for about 23,8 trillion euros. The difference between the 96 and 82 banks we consider consists of banks with less than four borrowing relations with NFCs per month. We drop these banks to enhance the robustness of the estimated bank supply components. These banks are European subsidiaries of large foreign banks specialising in businesses other than NFC lending.

[36] Controls include the ratio of credit under moratoria (as % of total assets), a dummy for RoA above the median, the NPL ratio, the ratio between risk-weighted assets and total assets, deposits (as % of total assets), the overall capital buffer (OCR), the distance to the maximum distributable amount, equity (as % of total assets), the P2G buffer, and a dummy for significant institutions. Summary statistics are described in Table F.1.

estimates of bank supply start in January 2020, we select it as $pre - covid$ date and December 2020 as $post - covid$ for $\widetilde{\beta}_{bc}$. Supervisory data are only quarterly, so we define December 2019 as $pre - covid$ for X_{bc}.

Table 2: Impact of capital buffer releases on idiosynchratic bank supply

	1		2		3		4	
Caprel	-19.98*	(-2.25)	-20.86*	(-2.22)	-21.81**	(-3.28)	-11.88+	(-1.82)
Credit guarantees (% TA)			4.915***	(5.06)	10.05***	(5.16)	2.559***	(5.29)
Credit moratoria (% TA)			22.60	(0.89)	22.64	(0.77)	3.111	(0.31)
RoA (> median dummy)					0.347*	(2.56)	0.113	(1.14)
NPL ratio					-3.112	(-1.68)	-0.283	(-0.49)
RW					1.036+	(2.02)	0.300+	(2.00)
Equity (% TA)					0.0369	(0.01)	1.539**	(3.72)
Deposits (% TA)					0.0841	(0.11)	0.275	(0.79)
OCR					-2.370	(-0.44)	-1.485	(-1.60)
Distance to MDA					-0.477	(-0.59)	0.524+	(2.05)
P2G							-3.203	(-1.32)
SI dummy							0.0478	(0.55)
N	81		81		79		275	
r2	0.230		0.241		0.454		0.264	
r2_a	0.0946		0.0804		0.253		0.196	
Country fixed effect	YES		YES		YES		YES	

Note: t statistics in parentheses. Data are winsorised at 0.01 percent level. Change in supply component ($\widetilde{\beta}^q_{bc,\,post} - \widetilde{\beta}^q_{bc,\,pre}$) as dependent variable. Standard errors clustered at country level. Columns 1 to 3 consider only significant institutions (SI), Column 4 includes a sample of less significant institutions (LSI) for which the data quality and completeness is the most reliable.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2 shows that $Caprel$ had a significant expansionary impact on the change in bank supply and that releases supported banks' continued lending during the pandemic, as did $Credit\ guarantees$. At the same time, banks may be reluctant to release buffers because of uncertainty about future replenishment paths. This uncertainty should be less relevant for more profitable banks. We investigate this hypothesis using a quantile regression specified as follows:

$$\begin{aligned}\widetilde{\beta}^q_{bc,\,post} - \widetilde{\beta}^q_{bc,\,pre} = \\ &\lambda_0 + \lambda_1 * Caprel^q_{bc} + \lambda_2 * RoA^q_{bc} + (\lambda_3 * Caprel^q_{bc} \times High\ RoA^q_{bc}) + \\ &\lambda_4 * Credit\ guarantees^q_{bc,\,post} + \lambda_5 * X^q_{bc,\,pre} + \epsilon^q_{bc,\,pre} \end{aligned} \tag{9}$$

Where $High\ RoA^q_{bc}$ is a binary variable equal to one for values above the median. Table 3 shows that the interaction between releases and profitability is strongest for banks that most expanded credit supply. On the other hand, $Creditguarantees$ positively impact bank supply, especially on the lower end of the quantile distribution.[37] We also find that higher equity and higher distance to the Maximum Distributable Amount (MDA) have a positive impact among the banks that increase credit supply the most.

Table 3: Impact of releases across quantiles

	0.1		0.3		0.5		0.7		0.9	
Caprel	2.351	(0.16)	0.964	(0.11)	6.022	(1.02)	8.483	(1.41)	12.86	(1.54)
RoA	19.05	(0.55)	15.24	(0.88)	19.38	(1.00)	24.14	(1.00)	8.839	(0.55)
Caprel × RoA (> median dummy)	-5.555	(-0.14)	-13.54	(-1.07)	-13.56^{+}	(-1.75)	-15.10*	(-2.05)	-27.62***	(-4.26)
Credit guarantees (% TA)	4.796***	(4.20)	2.302***	(4.16)	1.254*	(2.54)	-0.0933	(-0.20)	-2.053*	(-2.07)
Credit moratoria (% TA)	16.29**	(2.71)	-6.814	(-1.43)	-11.60***	(-3.86)	-2.968	(-0.45)	-0.218	(-0.01)
NPL ratio 1	-0.103	(-0.25)	0.204	(1.29)	0.205	(1.14)	0.425	(0.83)	1.414***	(5.14)
RW	1.414***	(3.69)	0.486^{+}	(1.92)	0.418**	(2.82)	0.174	(1.31)	-0.00598	(-0.05)
Equity (% TA)	0.793	(1.11)	0.527	(0.85)	0.631^{+}	(1.89)	0.467^{+}	(1.74)	1.643***	(3.59)
Deposits (% TA)	1.442*	(2.37)	0.121	(0.93)	0.0676	(0.36)	0.106	(1.22)	0.414***	(4.69)
OCR	0.0757	(0.03)	-0.531	(-0.33)	-0.109	(-0.11)	-0.974	(-1.24)	0.0698	(0.05)
Distance to MDA	0.878	(0.85)	0.303	(0.43)	0.343	(1.20)	0.101	(0.96)	1.088^{+}	(1.70)
P2G	-4.326	(-0.50)	-4.777*	(-2.11)	-0.441	(-0.26)	-0.862	(-0.60)	-2.038	(-0.50)
SI dummy	0.261***	(4.00)	0.0317	(0.52)	0.00419	(0.07)	0.00888	(0.22)	0.0919*	(2.28)
N	275		275		275		275		275	
r2	0.0922		0.111		0.103		0.0959		0.0757	

Note: t statistics in parentheses. Data are winsorised at 0.01 percent level. Quantile regression, change in supply component ($\widetilde{\beta}^{q}_{bc,\,post} - \widetilde{\beta}^{q}_{bc,\,pre}$) as dependent variable. Standard errors clustered at country level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Conclusion

The macroprudential toolkit includes a variety of policies, both of broad and targeted nature. However, few tools exist to guide policymakers in identifying the correct measures and policy implementation timing. This paper uses the well-known AW decomposition of credit dynamics to inform the discussion ex-ante on policy choice and ex-post on policy evaluation. We apply it to the granular AnaCredit dataset to decompose credit growth between a common component, a supply and a demand component. The common component captures the median credit growth across banks and borrowers, so a high value would call for the activation of broad-based instruments. The demand (supply) component informs on possible heterogeneity across borrowers (lenders), so a considerable value would suggest activating more targeted measures.

Furthermore, we show that decomposition can be used in econometric studies to assess the impact of macroprudential measures. By identifying the idiosyncratic supply component, the decomposition allows for a clean assessment of the drivers and the effects of policy measures. In this respect, we determine that capital requirement releases had an expansionary impact on

[37] We also evaluate the distribution of variables around the different quantiles and find no significant sub-sample bias.

bank credit supply during the Covid-19 crisis. Moreover, the effect is more extensive on average for more profitable banks.

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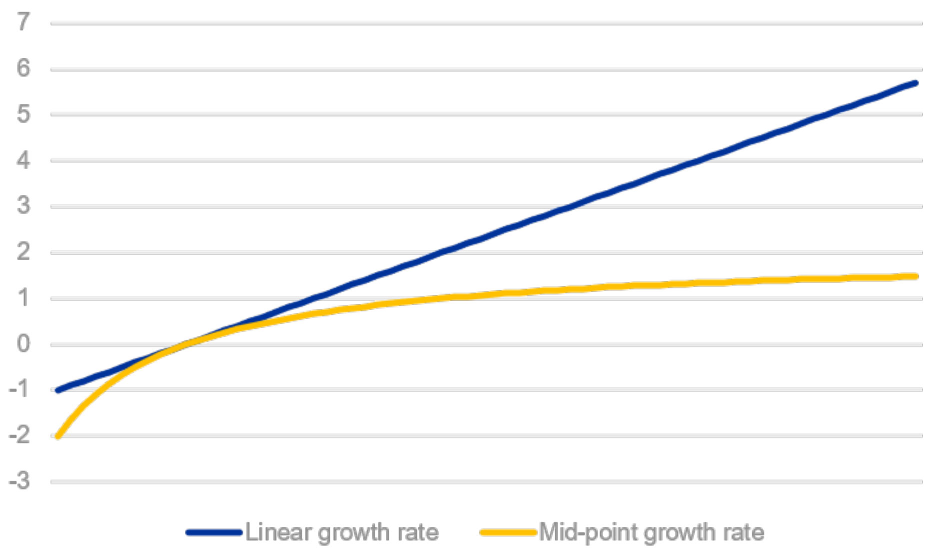
A Data and methodology

Table A.1: Average volume of AnaCredit data included in the estimation through single-bank clustering

Country	Average % of single-bank firms per month	Average % volume without single-bank firms per month	Average % volume after clustering per month	Average number of banks per month	Average number of firms per month	Average number of loans per month
AT	79.76	63.28	100	345	16863	107721
BE	84.07	51.16	98.1	90	41270	190366
DE	68.18	71.76	87.94	956	209352	1213461
ES	64.94	77.6	98.52	182	197687	1289073
FI	84.6	58.66	98.56	44	23612	103676
FR	85.34	62.96	89.45	178	261737	1279570
GR	70.15	75.05	99.62	36	19590	98208
IE	87.83	42.2	64.61	42	3529	16811
IT	62.46	84.93	99.07	170	333262	2054077
LU	81.98	71.18	99.97	66	2369	12714
NL	87.63	70.62	99.72	109	16936	77354
PT	64.68	75.95	98.27	72	38133	223715

Figure A.1: Comparison between linear and mid-point growth rate



B Contribution of components to the aggregate credit growth

To better identify the contributions of the components to the aggregate credit growth rate, we regress each component of Eq. 3 on the aggregate growth rate to study its contribution in the following way:

$$Component_t = \beta_0 + \beta_1 D_t + \epsilon_t \tag{B.1}$$

Results are shown in Table B.1 and confirm that countries tend to have either a significant common component or supply and demand components. Therefore, we are able, with our decomposition, to identify and track changes in credit drivers in time.

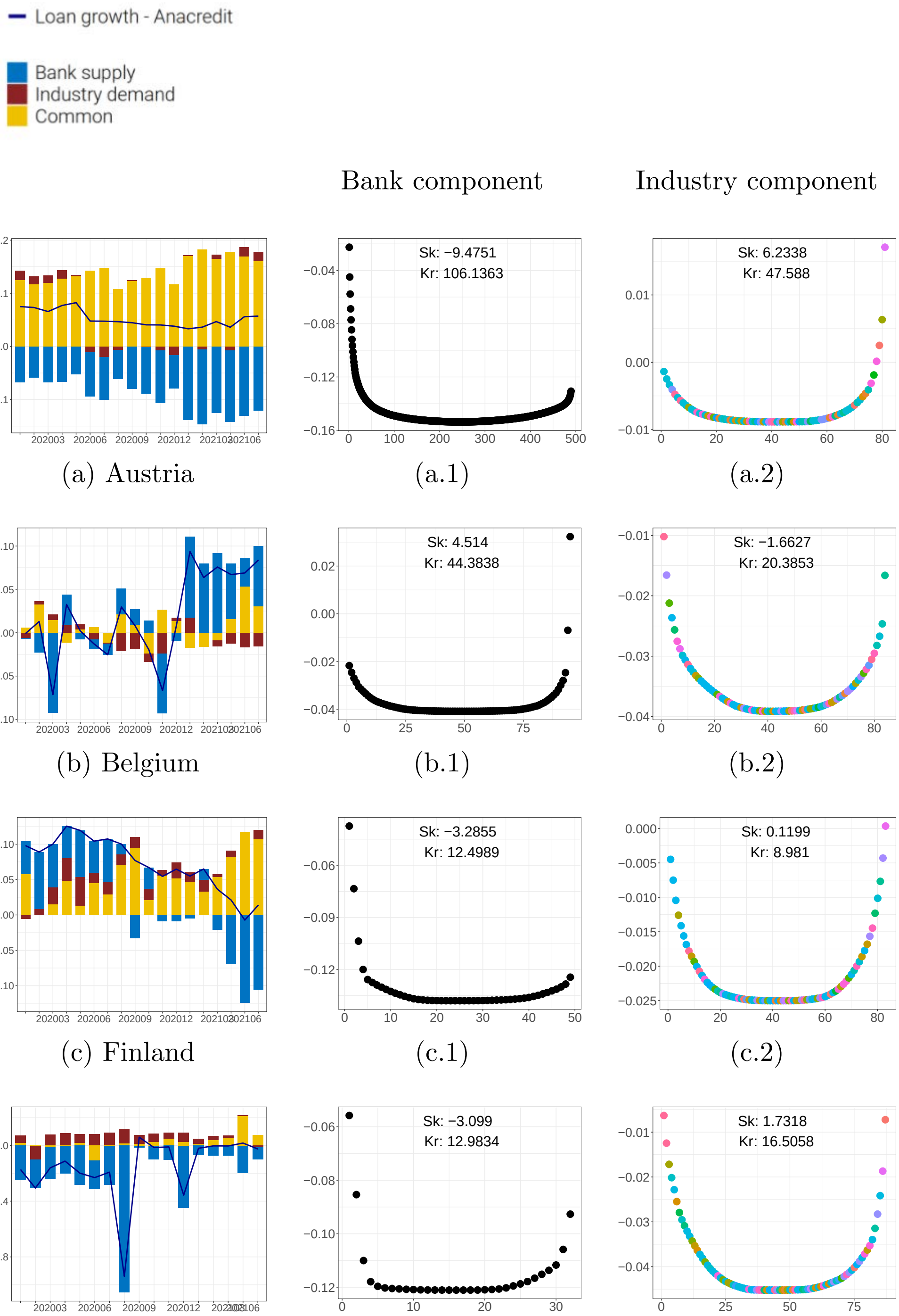
Table B.1: Contribution of components to the aggregate credit growth

Country	Bank	Firm	Common
AT	0.6254+	1.2268***	-0.8522
	(0.3545)	(0.2212)	(0.5358)
BE	0.8378+	0.6351*	-0.4729
	(0.4509)	(0.2246)	(0.3568)
DE	0.5499***	0.4329***	0.0172
	(0.0912)	(0.0871)	(0.0986)
ES	0.1676	-0.3957	1.2281***
	(0.4061)	(0.3502)	(0.2744)
FI	0.7404	0.665**	-0.4053
	(0.7652)	(0.1836)	(0.8939)
FR	0.933***	-0.8167**	0.8838*
	(0.1586)	(0.2157)	(0.3092)
GR	-0.2807	1.0681***	0.2126
	(0.2136)	(0.18)	(0.2257)
IE	0.9933***	0.2595	-0.2528+
	(0.1703)	(0.2047)	(0.1432)
IT	-0.0872	0.0876	0.9996***
	(0.1304)	(0.2215)	(0.2337)
LU	0.0655	0.8009	0.1336
	(0.4361)	(0.4966)	(0.2638)
NL	0.9015	-0.2532	0.3517
	(0.5887)	(0.3584)	(0.6042)
PT	0.8779**	-0.624+	0.746**
	(0.2384)	(0.3032)	(0.1909)

Note: standard errors in parenthesis.

C Credit growth components (Additional material)

Figure C.1: Credit growth decomposition and distribution of the idiosyncratic components



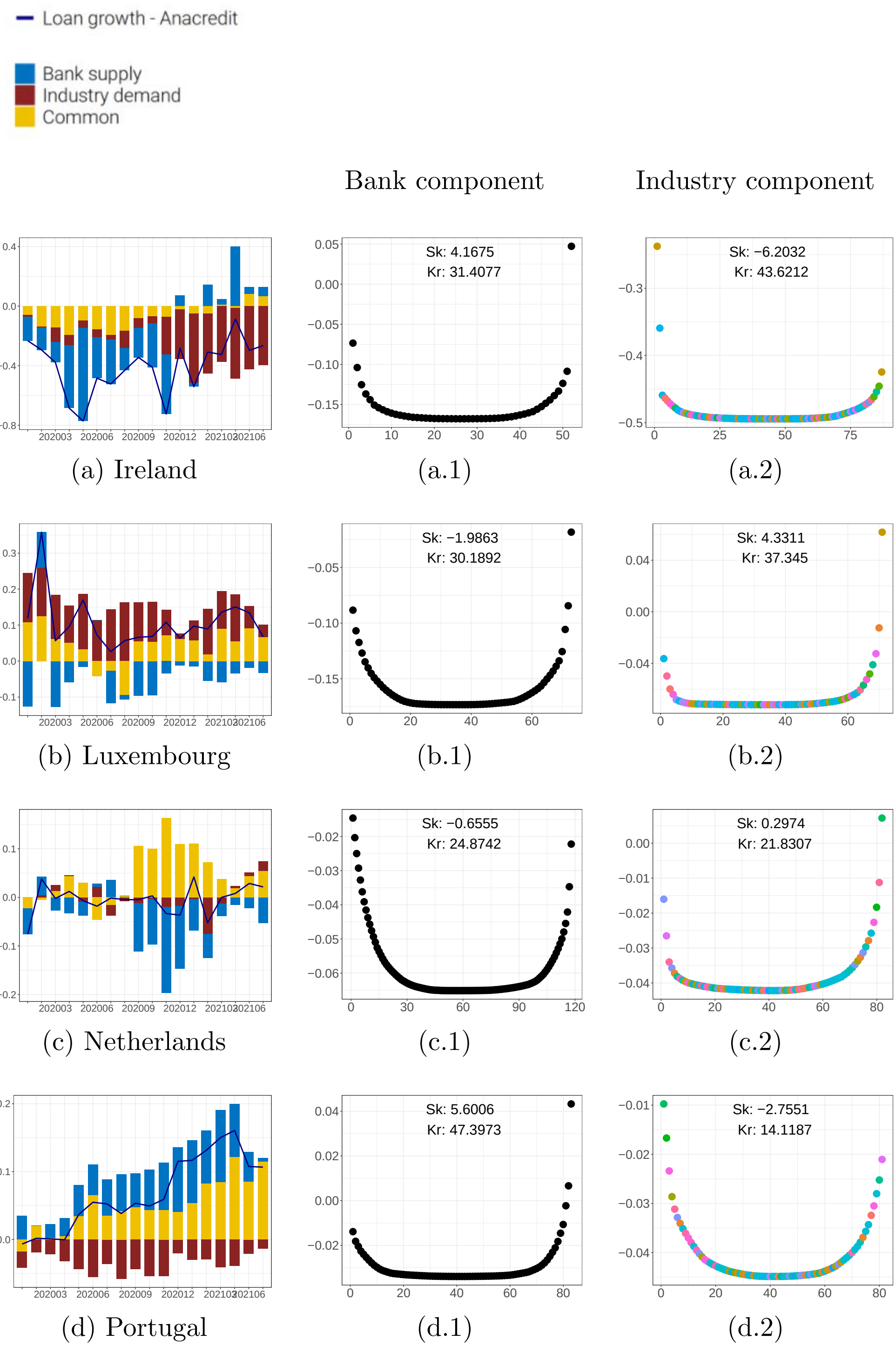
(a) Austria (a.1) (a.2)

(b) Belgium (b.1) (b.2)

(c) Finland (c.1) (c.2)

(d) Greece (d.1) (d.2)

Figure C.2: Credit growth decomposition and distribution of the idiosyncratic components



D Validation: components and interest rates

We show that the idiosyncratic supply and demand components also square with standard assumptions surrounding loan pricing (see the mainstream relationship between interest rates and quantity of credit in e.g. Hicks, 1937, 1980). We propose two pieces of evidence that extend the robustness checks presented by the literature. Our first test investigates the correlation between interest rates and the idiosyncratic supply and demand components. Exploiting the granularity of AnaCredit, we compute the weighted interest rate for each bank-firm pair.[38] We thus regress the interest rates on our components for the pre-Covid period as follows:

$$ir_{fbc} = \alpha + \beta * Supply\ component_{bc} + \beta * Demand\ component_{fc} + c_c + \epsilon_{fbc} \tag{D.1}$$

$$ir_{fbc} = \alpha + \beta * Supply\ component_{bc} + \gamma * yield10y_c + \theta_{fc} + c_c + \epsilon_{fbc} \tag{D.2}$$

$$ir_{fbc} = \alpha + \beta * Demand\ component_{fc} + \gamma * yield10y_c + \phi_{bc} + c_c + \epsilon_{fbc} \tag{D.3}$$

where ir_{fbc} is the weighted interest rate for the relationship between bank b in country c and firm f; c_c is the vector of country fixed effects; θ_{fc} is the set of firm fixed effects per country; and ϕ_{bc} is the set of banks fixed effects per country. Our main model is Eq. D.1, while we maintain Eq. D.2 and Eq. D.3 as main robustness checks.

Table D.1: Credit decomposition components and interest rates (February 2020)

	1	2	3	4	5	6	7
Supply component ($\widetilde{\beta}_{bct}$)	-0.00872^{+}	-0.00777^{+}			-0.00668***	-0.00679^{+}	
Demand component ($\widetilde{\alpha}_{fct}$)			0.00566***	0.00572***	0.00561***		0.00543***
$yield10y_{country\ of\ bank}$						0.00432*	
$yield10y_{country\ of\ firm}$							0.00420***
Constant	0.0326***	0.0327***	0.0326***	0.0326***	0.0325***	0.0313***	0.0314***
N	1288475	889522	1288475	1288465	1288475	885740	1285957
r2	0.130	0.603	0.139	0.203	0.140	0.617	0.204
r2_a	0.130	0.374	0.139	0.202	0.140	0.396	0.203
Country fixed effects	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	NO	NO	NO	YES	NO	NO	YES
Firm fixed effects	NO	YES	NO	NO	NO	YES	NO
Clustered std. err.	Bank	Bank	Firm	Firm	Robust	Bank	Firm

Data are winsorised at 0.01 percent level.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[38] Notice that here, as it is throughout the paper, we consider firms either multi-bank firms or clusters of single-bank firms.

Table D.1 shows our main results for a cross-section extracted for February 2020. We find that the idiosyncratic supply component is negatively correlated with interest rates. An increase in 1% in the supply component predicts on average a decline of 0.66 basis points in the interest rates in the same month (Table D.1, Column 5). The demand component, as expected, is positively correlated with the interest rates and a 1% increase in demand yields an interest rate increase of 0.56 basis points on average.

Regressions are not simultaneous as the components are estimated using year-to-year growth rates while interest rates are collected for February 2020. As robustness, we also test whether the correlation is confirmed at different points in time (January 2020) (Table D.2) and when adding lags to the components (Table D.3). The bank supply component continues to be negatively correlated with the interest rate.[39]

We think that the evidence we provide extends the validation of the AW components that have been proposed so far in the literature. Our results show that the bank supply component is negatively correlated with the interest rate as is theoretically expected. The demand component, also in line with theory, is positively correlated with the interest rates.

Table D.2: Credit decomposition components and interest rates (January 2020)

	1	2	3	4	5	6	7
Supply component ($\widetilde{\beta}_{bct}$)	-0.00637	-0.00671			-0.00381***	-0.00518	
Demand component ($\widetilde{\alpha}_{fct}$)			0.00561***	0.00561***	0.00560***		0.00531***
$yield10y_{country\ of\ bank}$						0.00368*	
$yield10y_{country\ of\ firm}$							0.00344***
Constant	0.0326***	0.0327***	0.0328***	0.0328***	0.0328***	0.0307***	0.0310***
N	1301438	899125	1301438	1301428	1301438	895276	1298897
r2	0.126	0.601	0.136	0.200	0.136	0.615	0.201
r2_a	0.126	0.372	0.136	0.199	0.136	0.394	0.201
Country fixed effects	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	NO	NO	NO	YES	NO	NO	YES
Firm fixed effects	NO	YES	NO	NO	NO	YES	NO
Clustered std. err.	Bank	Bank	Firm	Firm	Robust	Bank	Firm

Data are winsorised at 0.01 percent level.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[39] In the cross section for January, a 1% increase in the supply component predicts on average a decrease of 0.38 basis point in the interest rate (Table D.2, Column 5), while an increase of 1% of the supply component in January predict on average a decrease of 0.32 basis point in the interest rate in February 2020 (Table D.3, Column 5). Holding supply constant, an increase of 1% of the demand component in January 2020 predicts on average an increase of 0.56 basis points in the interest rates in January 2020 and of 0.563 in February 2020.

Table D.3: Credit decomposition components and interest rates (measured in January and February 2020, respectively)

	1	2	3	4	5	6	7
Supply component ($\widetilde{\beta}_{bct}$)	-0.00579	-0.00632			-0.00327***	-0.00477	
Demand component ($\widetilde{\alpha}_{fct}$)			0.00563***	0.00567***	0.00563***		0.00537***
$yield10y_{country\ of\ bank}$						0.00364*	
$yield10y_{country\ of\ firm}$							0.00354***
Constant	0.0326***	0.0328***	0.0328***	0.0328***	0.0328***	0.0307***	0.0310***
N	1281737	881337	1281737	1281727	1281737	877575	1279226
r2	0.129	0.603	0.138	0.203	0.139	0.617	0.204
r2_a	0.129	0.375	0.138	0.202	0.139	0.396	0.203
Country fixed effects	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	NO	NO	NO	YES	NO	NO	YES
Firm fixed effects	NO	YES	NO	NO	NO	YES	NO
Clustered std. err.	Bank	Bank	Firm	Firm	Robust	Bank	Firm

Data are winsorised at 0.01 percent level.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Firm credit demand during the pandemic

In this section, we show that firms with more liquidity demanded relatively less credit during the pandemic, confirming that liquidity needs primarily drove the surge in lending. We also find some evidence that, with the crisis, larger firms increasingly tilted their credit demand away from banks.

To study the determinants of firm demand, we investigate whether (and how) firms' balance-sheet characteristics associated with a larger demand for credit evolved with the pandemic. We combine our demand component, estimated in February 2020, with ORBIS data for 2019.[40] The data covers 768,126 firms (approximately 66% of the firms used in the decomposition), with the largest number of enterprises concentrated in Italy; in terms of firms' total assets, Germany, France, Italy, Spain, and the Netherlands are the most represented (Figure E.1). From previous studies,[41] we expect more liquid firms to demand less credit (Falagiarda et al., 2020) and SMEs to demand more (see e.g. Khwaja and Mian, 2008; Chodorow-Reich et al., 2021). Our cross-sectional regression is defined as follows:

$$\widetilde{\alpha}_{fc,\,pre} = \lambda_0 + \lambda_1 * Z_{fc,\,pre} + \epsilon_{fc,\,pre} \tag{E.1}$$

where $\widetilde{\alpha}_{fc,\,pre}$ is the demand component in February 2020; and $Z_{fc,\,pre}$ is a set of firm characteristics.[42]

We find that, in general, a higher return on assets, a larger sales ratio, a long-term debt ratio, and loans' ratio are associated with higher demand (Table E.1). On the contrary, higher liquidity ratios, capital, and interest rate expenses predict a lower demand for credit as expected from previous studies. Moreover, regarding firm size, large firms' demand is lower than that of medium-sized firms, while small and micro enterprises demand on average more credit.

To assess how the pandemic has changed firm financing behaviour, we regress the quarterly demand components on the firms' characteristics of December 2019. In Table E.2 we show that the impact of profitability, measured by RoA, grows over time. Firms that were more profitable

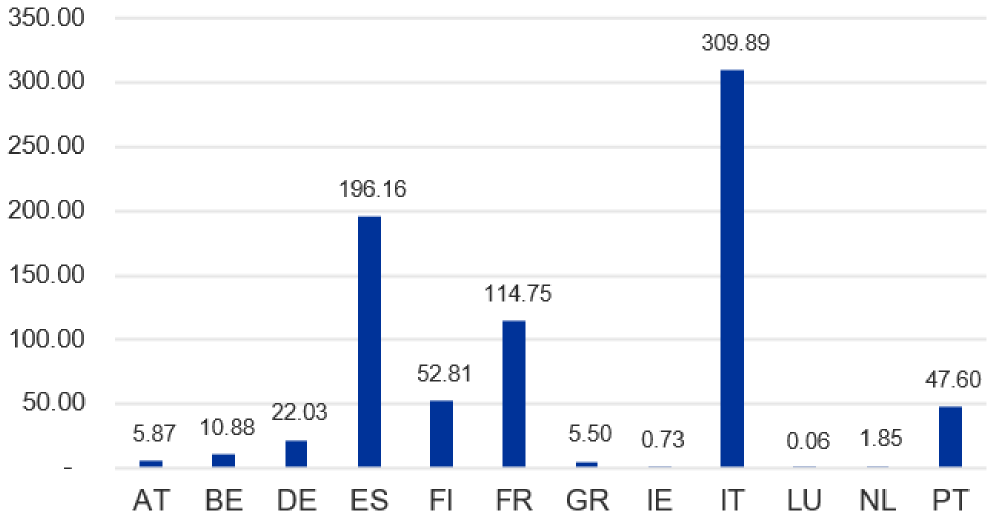
[40] As anticipated in Section 2, we adopt here an industry-location clustering for single-bank firms to better match the decomposition with firm-level data.

[41] Many studies that exploit loan-level data focus on the impact of bank supply shocks: on firms' investment Amiti and Weinstein (2018) and Amador and Nagengast (2016), on firms' productivity Manaresi and Pierri (2018), and on employment and outputAlfaro et al. (2021).

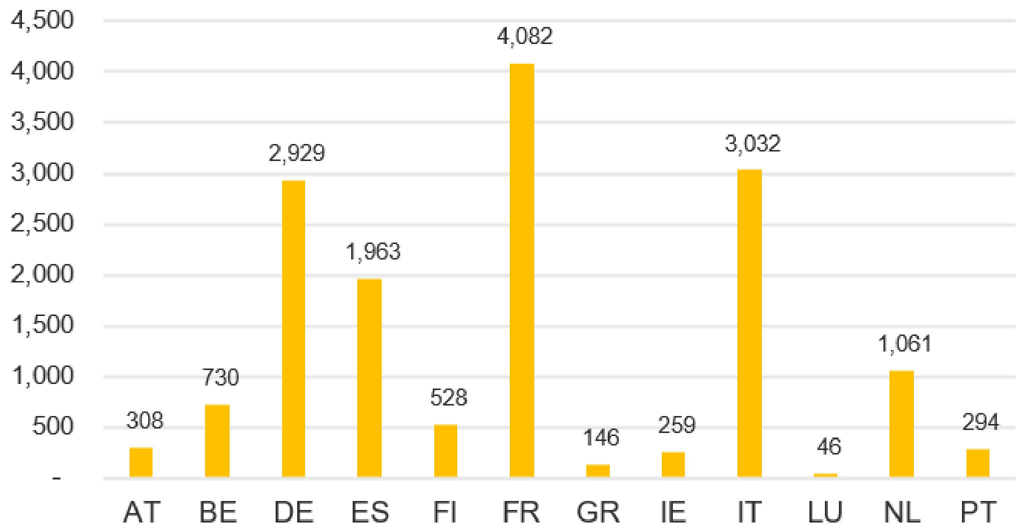
[42] As firms' characteristics, we include ROA, liquidity ratio, total assets (log), sales (as % of total assets), capital (as % of total assets), loans (as % of total assets), and interest rate costs (as % of total assets). We also include a dummy for large firms and a dummy for small or micro firms.

Figure E.1: Firm sample after merge with ORBIS

(a) Firms per country (thousands)



(b) Firms' total assets per country (billions)



Source: ECB (Anacredit) and ORBIS, authors' calculation)

Table E.1: Determinants of firm demand components

	All	Trade	Construction	Real estate	Manufacture	Transport	Services
RoA	0.010**	0.024**	0.017***	-0.007	0.010	0.024**	-0.002
	(3.83)	(3.25)	(9.69)	(-0.98)	(1.05)	(3.72)	(-0.54)
Liquidity ratio	-0.013*	-0.018*	-0.022***	-0.011**	-0.031*	-0.015+	0.009
	(-2.58)	(-2.82)	(-5.77)	(-3.61)	(-2.70)	(-2.06)	(1.69)
Tot. asset (log)	0.044***	0.064***	0.062**	0.044*	0.052***	0.005	0.066***
	(7.19)	(5.77)	(4.26)	(3.07)	(5.48)	(0.41)	(9.10)
Sales (% TA)	0.028*	0.025**	0.084*	0.018	0.021+	0.025	0.023**
	(2.36)	(4.07)	(2.84)	(1.39)	(2.05)	(1.57)	(4.62)
Capital (% TA)	-0.030***	-0.020***	-0.062***	-0.031***	-0.035*	-0.027*	-0.022*
	(-7.48)	(-4.86)	(-5.92)	(-11.64)	(-2.57)	(-3.11)	(-2.58)
Loans (% TA)	0.043*	0.050*	0.076**	0.004	0.047**	0.050***	0.038
	(2.73)	(2.55)	(3.30)	(0.37)	(3.81)	(4.87)	(1.75)
Int. rate costs (% TA)	-0.010*	-0.009*	-0.009	0.004	-0.003	-0.028	-0.031**
	(-2.64)	(-3.01)	(-0.65)	(0.39)	(-0.29)	(-1.73)	(-4.23)
Large firm dummy	-0.022***	-0.018**	-0.032*	0.002	-0.022**	-0.032***	-0.033***
	(-10.69)	(-4.39)	(-2.99)	(0.26)	(-3.94)	(-9.91)	(-11.22)
Small firm dummy	0.029**	0.037***	0.009	0.049**	0.042***	0.052**	0.024
	(3.44)	(4.72)	(0.73)	(4.56)	(6.96)	(4.17)	(1.11)
N	617746	154255	73516	43481	50975	23398	43017
r2	0.030	0.024	0.048	0.086	0.020	0.021	0.014
r2_a	0.030	0.024	0.048	0.085	0.020	0.020	0.013
Country fixed effects	YES	YES	YES	YES	YES	YES	YES
Sector fixed effects	YES	YES	NO	NO	NO	NO	NO

Standardized beta coefficients. Note: Std. err. clustered at firm-level. "Trade" refers to NACE2 45-46-47 (Motor wholesale and retail, wholesale, and retail trade), "Construction" refers to NACE2 41-43 (Construction of buildings, and specialised construction), "Real estate refers to NACE2 68, "Manufacture refers to NACE2 10-25-28 (manufacture of food, machinery and equipment, and metal products), "Service refers to NACE2 56-77-79-81-96 (Food and beverages, rental and leasing, travel, building, and other service activities). Standard errors clustered at firm level. Data are winsorised at 0.01 percent level. OLS, demand component $\widetilde{\alpha}_{fc,\,pre}$ as dependent variable

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.2: Determinants of firm demand components over time

	Feb-20		Jun-20		Sep-20		Dec-20	
RoA	0.010**	(3.83)	0.026***	(7.98)	0.032***	(11.36)	0.037***	(11.97)
Liquidity ratio	-0.013*	(-2.58)	-0.018***	(-6.35)	-0.016***	(-5.60)	-0.015**	(-3.88)
Tot. asset (log)	0.044***	(7.19)	-0.016	(-0.84)	-0.028*	(-2.26)	-0.046*	(-2.73)
Sales (% TA)	0.028*	(2.36)	0.051+	(2.20)	0.060*	(2.39)	0.063*	(2.36)
Capital (% TA)	-0.030***	(-7.48)	-0.023***	(-5.09)	-0.016*	(-2.67)	-0.012+	(-1.87)
Loans (% TA)	0.043*	(2.73)	0.013	(1.08)	-0.011	(-0.98)	-0.024*	(-2.23)
Int. rate costs (% TA)	-0.010*	(-2.64)	-0.032***	(-6.58)	-0.030***	(-4.50)	-0.022***	(-5.28)
Large firm dummy	-0.022***	(-10.69)	-0.030***	(-7.37)	-0.032***	(-7.54)	-0.023***	(-6.20)
Small firm dummy	0.029**	(3.44)	0.015	(1.77)	0.008	(1.22)	0.008	(1.02)
N	617746		672564		677597		688051	
R2	0.030		0.063		0.094		0.106	
adj-R2	0.030		0.062		0.094		0.106	
Industry fixed effects	YES		YES		YES		YES	
Country fixed effects	YES		YES		YES		YES	

Note: Standardized beta coefficients. Standard errors clustered at firm-level. Data are winsorized at 0.01 level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. OLS, demand component $\widetilde{\alpha}_{fc,pre}$ as dependent variable

in 2019 demanded on average more liquidity in December 2020 than in February or June 2020. Small and micro firms demanded on average more credit before the pandemic, but their demand converged with that of other firms as the pandemic ensued. Larger firms, on the contrary, demand on average less bank credit over the quarters, suggesting that they may have increased the substitution of bank credit with other sources of financing over the period.

F Summary statistics of the econometric applications

Table F.1: Summary statistics

	Mean	SD	Count	Min	p25	p50	p75	Max
AnaCredit (February 2020)								
Loan interest rate (ir_{fbc})	0.0327	0.0247	1288475	0.0005	0.0159	0.0260	0.0422	0.1297
Supply component ($\widetilde{\beta}_{bct}$)	-0.0173	0.1279	1288475	-0.4124	-0.0928	-0.0178	0.0501	0.5763
Demand component ($\widetilde{\alpha}_{fct}$)	0.0097	0.8243	1288475	-2.0489	0.0064	0.1877	0.3482	1.5899
$yield10y_{country\ of\ bank}$	0.2994	0.5759	1283999	-0.4336	-0.1801	0.2692	0.9585	1.0657
$yield10y_{country\ of\ firm}$	0.2989	0.5761	1285967	-0.4336	-0.1801	0.2692	0.9585	1.0657
AnaCredit and superivisory data								
Change in supply component ($\widetilde{\beta}_{bc,post} - \widetilde{\beta}_{bc,pre}$)	-0.0519	0.3575	286	-1.4908	-0.1016	-0.0124	0.0905	0.8718
Caprel	-0.0037	0.0041	286	-0.0160	-0.0050	-0.0025	-0.0002	0.0000
Credit guarantees (% TA)	0.0078	0.0151	285	0	0	0.0002	0.0052	0.0656
Credit moratoria (% TA)	0.0006	0.0013	285	0	0	0.0001	0.0005	0.0076
RoA	0.0009	0.0011	285	-0.0028	0.0003	0.0007	0.0013	0.0041
NPL ratio	0.0343	0.0505	285	0.0001	0.0098	0.0181	0.0334	0.2875
RW	0.4200	0.1216	286	0.1891	0.3356	0.4186	0.4890	0.8074
Equity (% TA)	0.0288	0.0449	275	0	0.0035	0.0114	0.0365	0.4075
Deposits (% TA)	0.7777	0.1607	285	0.1246	0.7308	0.8377	0.8833	0.9322
OCR	0.1109	0.0148	286	0.0850	0.1	0.1097	0.119	0.1527
Distance to MDA	0.0598	0.0584	286	0.0065	0.0292	0.0450	0.0690	0.3659
P2G	0.0054	0.0093	286	0	0	0	0.01	0.05
AnaCredit and ORBIS data								
Demand component	0.0812	0.3374	868705	-0.5019	-0.1307	0.0437	0.2372	0.8969
RoA	3.5529	11.4980	843460	-100	0.25	2.25	6.95	100
Liquidity ratio	1.9763	4.7861	854563	0	0.59	1.06	1.78	100
Tot. asset (log)	13.7805	1.6631	868705	10.8198	12.5843	13.5778	14.7226	26.0645
Sales (% TA)	1.4489	1.5578	856439	-0.0266	0.5738	1.1791	1.9234	469.8179
Capital (% TA)	0.0869	0.2512	867294	-40.6354	0.0117	0.0318	0.0869	128.9468
Loans (% TA)	0.0640	0.1438	856031	-1.5399	0	0.0030	0.0795	35.9271
Int. rate costs (% TA)	0.0104	0.0390	769545	-0.0730	0.0023	0.0064	0.0136	19.4652

Data are winsorised at 0.01 percent level.

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