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Determinants of bank performance: evidence from replicating portfolios

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This paper contains research conducted within the network "Challenges for Monetary Policy Transmission in a Changing World Network" (ChaMP). It consists of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB).

ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Melina Papoutsi and Gonzalo Paz-Pardo (both ECB), 7 central bank advisers and 8 academic consultants.

ChaMP seeks to revisit our knowledge of monetary transmission channels in the euro area in the context of unprecedented shocks, multiple ongoing structural changes and the extension of the monetary policy toolkit over the last decade and a half as well as the recent steep inflation wave and its reversal. More information is provided on its website.

Abstract

We construct a novel measure of bank performance, investigate its determinants, and show that it affects bank resilience, lending behaviour and real outcomes. Using confidential and granular data, we measure performance against a market-based benchmark portfolio that mimics individual banks' interest rate and credit risk exposure. From 2015 to mid-2022, euro area banks underperformed market benchmarks by around €160 billion per year, amid substantial heterogeneity. Structural factors, such as cost inefficiencies, rather than monetary or regulatory measures, were the main driver of bank underperformance. We also show that higher edge banks are less reliant on government support measures and less likely to experience the materialisation of interest rate or credit risk when hit by shocks. Using the euro area credit register and the pandemic shock for identification, we find that higher edge banks originate more credit, direct it towards more productive firms, and support more firm investment.

JEL codes: E52, G12, G21, G28.

Key words: banking, maturity transformation, replicating portfolio, credit supply.

Non-technical summary

Over the last two decades, the low performance of euro area banks relative to their U.S. peers has raised concerns among policy makers and increasing interests among researchers. Banks' ability to generate adequate profits is crucial for the transmission of monetary policy. Profitable banks are able to attract capital from market investors and to generate capital internally through retained earnings. Higher bank performance enhances the capacity of the banking system to provide credit to the economy when monetary policy is eased and to withstand shocks when monetary policy is tightened. Moreover, higher bank performance increases the efficiency of stabilisation policies, as a higher bank resilience also implies that there is a lesser need for public intervention in response to the manifestation of adverse scenarios.

In this paper we use granular confidential data to shed light on drivers and implications of bank performance. Specifically, the study answers three questions. First, how can we adequately measure banks' ability to generate profits? Second, what are the determinants? And third, how does bank performance affect bank resilience, lending behaviour and, ultimately, real outcomes?

First, we construct a novel measure of bank performance, which we label bank edge, comparing actual bank book returns against a market-based benchmark portfolio that mimics individual banks' interest rate and credit risk exposure. We obtain this new measure by using very granular information on individual banks' balance sheet composition across maturities, inception dates and risk levels. By benchmarking bank performance against market equivalents at a very granular level, this new measure provides a unique perspective on banks' edge over other investors' ability to originate profitable investment strategies. We calculate quarterly bank edges for a panel of around 100 large European banks from 2015 to 2023. We find that from 2015 to the start of the hiking cycle, the aggregate banking sector underperformed the market benchmark on average by around €160 billion per year, or 1 percent of equity, amid substantial heterogeneity across banks as the top 25 percent banks consistently outperformed the market. The increase in lending margins brought about by the higher interest rate environment since July 2022 closed this gap and turned it positive for virtually all banks.

Second, we assess the role of different factors of bank performance commonly considered in the literature. In particular, we look at regulation, competition, cost efficiency and monetary policy. To investigate these drivers, we exploit the panel nature of our data via local projections, and we identify the role of each factor isolating seemingly exogenous and idiosyncratic determinants of these factors that go beyond the impact via the net worth of banks. Our analysis shows that the predominant drivers of euro area banks' underperformance are structural: higher cost inefficiency and, to a lesser extent,

higher competition lead to more bank underperformance. Tighter regulation and monetary policy have no robust effect on bank edges. A one standard deviation increase in cost inefficiency, equivalent to a quarterly change of cost-to-income ratio of 14 percentage points, leads to a reduction in bank edges equal to 10 percent of their quarterly variation, or 19 basis points of bank equity.

Third, we assess whether bank edges correlate with bank resilience against adverse shocks and bank reliance on public support measures, supporting credit supply and the real economy. We find that banks with positive edges were half as reliant on public guarantees as banks with negative edges during the Covid-19 pandemic. We also find that banks with higher edges were less likely to experience the materialisation of interest rate or credit risk when hit by the March 2023 market turmoil. Importantly, when we sort banks according to their return on equity (ROE), there are no differences between high ROE banks and low ROE banks. This validates the bank edge as an ex-ante informative predictor of bank performance that is complementary to other measures. Moreover, we use the European credit register to identify the effect of bank edges on bank credit supply by comparing the credit supply of banks with different edge levels to the same borrower. This allows us to isolate the differential impact of a bank edge onto its supply of loans to firms. We find that each percentage point of higher bank edge is associated with a 3 percent higher loan volume for the same borrower, especially for more productive firms. We then make use of the higher loan volumes predicted by higher edges to explain firm investments over the Covid-19 pandemic. We find that firms more exposed to high edge banks were able to sustain higher investment rates. The improvement in bank edges via cost efficiency gains led to a 3 percent expansion in credit supply and 9 percent higher firm investment.

1 Introduction

The performance of the banking sector influences banks' intermediation capacity, the transmission of prudential and monetary policy, as well as firms' ability to invest in innovative projects. Measuring this performance and its drivers is, therefore, of paramount importance for understanding the resilience of the banking sector and the economy to shocks. Using available indicators of bank performance suggests that in the last 15 years European banks have been struggling. Since 2008, the price-to-book equity ratio of European banks, a commonly used valuation measure, has averaged well below one and well below that of their US peers. In addition, the return on book equity, a commonly used profitability measure, lags behind that of also struggling US peers. Post-crisis financial regulatory reform, non-bank competition, structural cost inefficiencies, and low interest rates are some of the many proposed explanations for low post-crisis bank valuation globally (e.g., Sarin and Summers, 2016; Buchak, Matvos, Piskorski, and Seru, 2018; Atkeson, d'Avernas, Eisfeldt, and Weill, 2019; Sarto and Wang, 2023).

In this study, we investigate the determinants of banking underperformance within the euro area, employing a comprehensive and confidential dataset from the European Central Bank (ECB). This study makes use of a novel performance metric, termed the 'bank edge', which assesses a bank's comparative advantage relative to a market-based and risk-adjusted benchmark portfolio. Unlike traditional performance metrics such as Return on Equity (ROE), this new measure captures distinct dimensions of bank performance. Our empirical findings suggest that the primary factors contributing to the underperformance of euro area banks are structural, predominantly driven by high operational expenses and intensified competition from non-bank financial institutions. Tighter regulation and monetary policy have no robust effect on banks' edge. We validate the bank edge as an ex-ante informative predictor of performance. Specifically, we demonstrate that banks with a higher 'bank edge' exhibit reduced dependence on governmental support mechanisms in the face of the Covid-19 pandemic and are less susceptible to the realization of interest rate or credit risks during the market disturbances of March 2023. Furthermore, the analysis reveals that an elevated 'bank edge' correlates with a markedly increased provision of credit, particularly to more productive firms, which in turn translates into higher firm-level investment rates.

To construct the performance measure for each bank, we build on Begenau, Piazzesi, and Schneider (2015) and follow Begenau and Stafford (2019) by comparing the book return on each bank's individual portfolio position against a market-based benchmark fixed-income portfolio return that shares the same interest rate and credit risk characteristics as the bank position. The bank's edge is then just the difference between the two returns. This calculates a bond-market based edge that compares bank returns against

bond-market compensations for passive credit- and interest rate risk exposures. The edge is positive if banks achieve higher risk-adjusted returns than what an investor would earn for holding the same risks passively in the capital markets.

We compute the quarterly bank edges for a panel comprising 100 major European banks covering the period from 2015 to 2023. The exposure of these banks to interest rate and credit risks is determined through the analysis of our rich data. Data on individual bank balance sheet positions come from detailed nonpublic ECB supervisory data, which we supplement with detailed loan data from the euro area credit register (AnaCredit), detailed deposit data from individual bank balance sheet statistics (IBSI) and security level information for securities held from the Securities Holdings Statistics Group (SHSG), and for securities issued from the Centralized Securities Database (CSDB). Together, these data allow us to calculate each bank's interest rate and credit risk exposures. To construct the benchmark portfolio, we use the ECB's sovereign yield curves, the median government bond ratings provided by S&P, Moody's and Fitch, and the IHS Markit iBoxx capital market data. We calculate the edge of an individual bank as the difference of the actual returns and the replicating portfolio's returns. We then show that over our sample period euro area banks underperformed the benchmark by around €160 billion, or 1 percentage points of book equity, on average each year until the ECB's started increasing interest rates in July 2022. Since then, banks have on average outperformed the benchmark by around 2 percentage points. There is, however, large variation in the cross-section of banks. Although the top 25% of banks outperformed the benchmark by around 0.6 percentage points between 2015 and 2022 Q2, the bottom 25% underperformed it by around 5.6 percentage points in annualised terms in the same period. Following the sharp increase in interest rates since July 2022, both groups improved significantly, with the top 25% banks outperforming the benchmark by 7.8 percentage points until 2023 Q2, and the bottom 25% also outperforming by around 0.4 percentage points.

To investigate the drivers of low euro area bank performance, we exploit the panel nature of our data within a local projection-style regression framework, by predicting a bank's edge using measures of competition, regulatory intensity, cost-inefficiency, and monetary policy shocks. More intense competition and higher costs relative to bank income are associated with a reduction in banks' relative performance, while monetary policy has an ambiguous effect, and tighter regulation has no effect on bank edges. Given that banks exhibiting higher (lower) bank edges also have greater (lesser) net worth, and considering that net worth plausibly reflects a bank's cost efficiency and competitive standing, it is conceivable that the aforementioned outcomes might just be attributable to variations in net worth rather than to the 'bank edge' performance metric itself. To separate net worth and leverage effects from our performance mea-

sure, we orthogonalize each potential driver of the bank edge with respect to various measures of bank net worth. We then find that cost inefficiencies and to some lesser extent competition are the key drivers of bank edges. A one-standard deviation increase in the cost-to-income ratios of banks leads to a 19 basis point reduction in the bank edge, equal to 10% of its variation.

We assess whether bank edges correlate with bank resilience against adverse shocks and bank reliance on public support measures, thereby supporting credit supply and the real economy. We find that banks with positive edges were half as reliant on public guarantees as banks with negative edges during the Covid-19 pandemic. We also find that banks with higher edges were less likely to experience the materialisation of interest rate or credit risk when hit by the March 2023 market turmoil. Importantly, when we sort banks according to their return on equity (ROE), there are no differences between high ROE banks and low ROE banks. This validates the bank edge as an ex-ante informative predictor of bank performance that is complementary to other measures.

Higher bank edges are associated with larger bank credit supply and, ultimately, support higher investment rates by firms that borrow from high edge banks. We use the European credit register to identify the effect of bank edges on bank credit supply by comparing the credit supply of different banks with different edge levels to the same borrower. This allows us to isolate the differential impact of a bank's edge on its supply of loans to firms. We find that each percentage point of higher bank edge is associated with a 3% higher loan volume for the same borrower, especially for more productive firms. We then make use of the higher loan volumes predicted by the higher edges to explain firm investments during the Covid-19 pandemic. We find that firms more exposed to high-edge banks had higher investment rates. Improvement in bank edges through cost efficiency gains led to an expansion of 3% in credit supply and increased firm investment by 9%.

Related Literature Our work relates to several recent studies that examine bank performance, its determinants, and its interaction with monetary policy.

Recent work on bank performance in the United States includes Begenau and Stafford (2019), Sarin and Summers (2016, 2019) and Atkeson, d'Avernas, Eisfeldt, and Weill (2019). Our analysis is based on a unique and non-public collection of data provided by the ECB. These euro area-focused data have been used by numerous other studies focusing on different questions and topics.[1]

Standard bank performance measures are typically focused on book values[2] or market-based mea-

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[1]E.g., Altavilla et al. (2020, 2021b); Bubeck, Maddaloni, and Peydró (2020); Maddaloni and Peydró (2011); Peydró, Polo, and Sette (2021); Andreeva and García-Posada (2021)

[2]Book value measures include the return on assets (ROA), the return on equity (ROE), and narrower components of bank

sures.[3] Our performance measure combines bank accounting data on investment and funding positions together with market information on the returns and costs of those positions (e.g., Begenau, Piazzesi, and Schneider, 2015; Begenau and Stafford, 2019).[4] We calculate our bank performance measure as the difference between banks' return on equity and the benchmark return, that is, the cost of capital from the perspective of bank equity investors. As a result, our edge is similar to the economic value added (EVA) (e.g., Damodaran, 2007; Kimball, 1998), but one where each bank's cost of capital is calculated based on its positions as a levered fixed income portfolio.[5]

Our paper contributes to the literature on the impact of monetary policy on bank profitability (e.g., Flannery, 1981; Hancock, 1985; Bourke, 1989; Saunders and Schumacher, 2000; Claessens, Coleman, and Donnelly, 2018; Brunnermeier and Koby, 2018). While a monetary policy easing can reduce net interest income (NII) (Alessandri and Nelson, 2015; Borio, Gambacorta, and Hofmann, 2017) and therefore harm banks, it also lowers discount rates and therefore increases bank valuations (English, Van den Heuvel, and Zakrajšek, 2018). Monetary accommodation can improve bank profitability through a positive impact on loan loss provisions and non-interest income (Altavilla, Boucinha, and Peydró, 2018; Williams, 2020). Both channels explored in these strands of literature boil down to banks' exposure to interest rate or credit risk, which ultimately stem from the more favourable overall financing conditions induced by monetary policy easing. Our measure of bank performance, which explicitly controls for interest rate and credit risk, isolates that part of the impact of monetary policy more tightly linked, for instance, to banks' business models and practices.

We also shed further light on the relation between regulatory pressure and bank performance. Stricter bank regulation, through for instance regulatory requirements for bank capitalization, motivated by prudential considerations, may put downward pressure on bank performance as the cost of capital increases. This could be further exacerbated by agency problems between bank management and shareholders (Calomiris and Kahn, 1991; Diamond and Rajan, 2001). At the same time, higher capital levels may improve bank performance and value by improving monitoring incentives (Holmstrom and Tirole, 1997; Allen, Carletti, and Marquez, 2011; Mehran and Thakor, 2011). The balance between these factors may

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profitability like the net interest margin (NIM).

[3]Market-based measures include the total share return (TSR, the ratio of dividends and increase of the stock value over the market stock price), the price-to-earnings ratio (P/E, a ratio of the financial results of the company over its share price), the price-to-book value (P/B, which relates the market value of stockholders' equity to its book value), and the credit default swap (as a measure of bank default risk).

[4]See the discussion in Begenau et al. (2022) for reasons why to use both book and market values when studying banks.

[5]Evaluating bank performance is ultimately a matter of ranking financial intermediaries vis-à-vis a benchmark. Unobservable benchmarks explored in the literature are, for instance, measures of frontier efficiency (Berger and Humphrey, 1997) or of cost of equity (Altavilla et al., 2021a).

depend on the state of the economy or on individual banks' characteristics (Berger and Bouwman, 2013). We show that most of the relation between bank performance and regulatory requirements is associated to the impact of regulation on banks' net worth, whereas there is little relation between regulation and more structural components of bank performance.

Our set-up allows to evaluate the relation between competition and bank performance. On the one hand, higher competition lowers markups on loans and markdowns on deposits, lowering banks' margins and therefore franchise value (Berger and Hannan, 1989; Claessens and Laeven, 2004; Drechsler, Savov, and Schnabl, 2021). On the other hand, higher rates implied by higher market power increase riskiness of loan portfolios (adverse selection and moral hazard), eventually lowering risk-adjusted returns (Stiglitz and Weiss, 1981; Boyd and De Nicolo, 2005; Schaeck, Cihak, and Wolfe, 2009). For the specific case of competition by non-banks, these have already been identified as a consistent threat to the performance of euro area banks, especially in specific business areas. For instance, more than 60% of incumbents view fintechs as a challenge for income streams related to payment and settlement systems.[6] We show that competitive pressure from non-banks is negatively associated with bank performance.

Lastly, cost efficiency of euro area banks has been systematically associated with higher bank performance (Andersson et al., 2018) and has been identified as a key structural feature dragging down the euro area banking sector's performance.[7] We confirm this intuition under the lenses of our measure of structural performance for euro area banks, and assess what a higher level of cost efficiency may entail for the euro area banking sector's dependence on public support measures and the overall resilience of bank lending conditions to shocks.

2 Measuring banks' edge

We measure the edge of each bank by comparing its return on equity (return on a specific balance sheet item) against a market based fixed-income benchmark portfolio that is designed to approximate the bank's (bank balance sheet item's) interest rate and credit risk exposure (e.g., Begenau, Piazzesi, and Schneider, 2015; Begenau and Stafford, 2019). The idea is to compare a bank's performance against a passive market return that investors could have earned if they had held securities with a similar amount of interest rate and credit risk. Clearly, bank loans may be riskier and therefore command a higher return

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[6]See, e.g., the European Banking Authority's (EBA) 2018 report on the impact of FinTech on incumbent credit institutions' business models.

[7]See, e.g., the speech "Challenges for bank profitability" by Luis de Guindos, Vice-President of the ECB, at the OMFIF City Lecture in London on 1 May 2019.

than our capital market benchmark. For example, bank loans may also include a liquidity risk premium because most bank loans are not tradable. Banks may also earn a higher return than the capital market benchmark due to market power over bank dependent borrowers. They also may be able to fund themselves more cheaply. These, and related reasons, will bias us towards finding a positive edge, provided the costs of running the banking business are not too large.

2.1 Data

Bank Data Our analysis relies on various several confidential datasets maintained by the ECB. The core sample of banks are the around 100 large financial institutions in the euro area which are directly supervised by the ECB and hold around 60% of total assets of all euro area banks.[8] We use the ECB's Supervisory Reporting (SUP) data to obtain quarterly balance sheet and income statement data for each bank, which goes back to 2014 Q4. This determines the beginning of the sample period. This data contains information on the outstanding amounts and related income and expense flows for banks' main balance sheet positions. These include loans, deposits and securities. In addition, for loans it also includes information on the riskiness of around 50% of outstanding amounts (measured via regulatory risk weights, which is only available for assets assessed under the standardised approach).

We complement this SUP data with monthly bank balance sheet statistics (Individual Balance Sheet Items, IBSI), which start in July 2007 and cover around 300 banks in the euro area. The IBSI data has information about maturities and sector splits of bank loans and bank deposits. Further detailed information on maturity and risk for bank loans to firms comes from the euro area credit register (AnaCredit; see description below). For securities owned by banks, we rely on detailed data from the Securities Holdings Statistics Group (SHSG). This data is at the quarterly level and contains comprehensive information (i.e., outstanding amounts, rating, and maturity at the ISIN level) about securities held by around 150 euro area banks going back to 2013 Q4. On the liability side we use IBSI data for information about deposit maturity and the Centralized Securities Database (CSDB) for information about issued securities. The CSDB contains monthly, ISIN level data on all securities issued in the euro since September 2013 of which SHSG is a subsample. Further details on the data is described in Appendix A.

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[8]Banks which are considered "significant" financial institutions in the euro area are directly supervised by the ECB's Single Supervisory Mechanism (SSM) since 2015 instead of the national authorities in the euro area member states. The status is determined by the ECB and depends on the size, the economic importance and the extent of cross-border activities of the banks, and on whether it has received direct public financial assistance, see here for details from the SSM.

Credit Register   We use data from AnaCredit, the euro area credit register, maintained by the European System of Central Banks, covering close to the universe of corporate loans in the euro area. AnaCredit collects harmonized data on individual loans from all member states, whereby banks are required to report information on loans to firms for exposures above €25,000. Information is available at a monthly frequency since September 2018. For each loan, we observe the outstanding nominal amount, the applied interest rate, the probability of default of the borrower and the amount in arrears, among others. The data also includes a wide set of borrower attributes such as the sector of economic activity and geolocational data. We merge AnaCredit to our bank level observables.

Capital Markets Data   We use three difference sources to obtain yields and ratings of public and private sector bonds. For government bond yields, we use the ECB's sovereign yields curves, which are available for the euro aggregate as well as separately for all member states.[9] The government bond ratings are measured as the median of the respective country's rating by S&P, Moody's and Fitch.

For corporate yields and ratings, we use proprietary data from IHS Markit iBoxx, which provides instrument level data on the yield-to-maturity and rating for a broad set of fixed and zero coupon bonds.

2.2   Construction of Benchmark Portfolio Returns

Figure 1: **Overview of data availability by relevant balance sheet items**
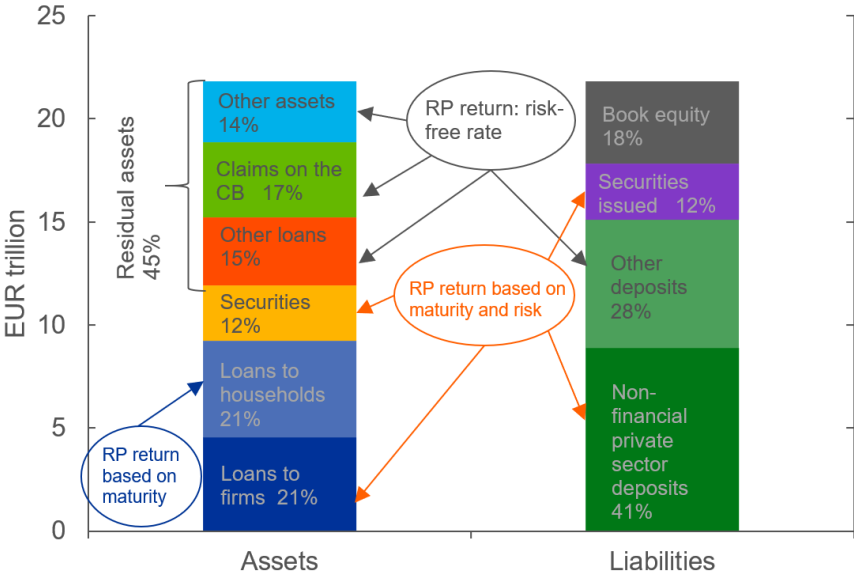
Notes: Composition of total assets/liabilities as of 2021 in our sample of euro area banks.

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[9]These are publicly available in the ECB's Statistical Data Warehouse .

We calculate the benchmark portfolio return for each bank and then aggregate. We focus on interest rate and credit risk exposure due to banks' role in maturity transformation and credit provision. This naturally exposes banks to duration and credit risk. The benchmark portfolio returns are calculated in two steps. First, we extract information about banks' balance sheet duration from the cash-equivalent share and average maturity for the individual balance sheet positions. Second, we select a bond portfolio that features approximately the same interest rate and credit risk exposure as implied by a specific balance sheet position. Then we compute the return of this portfolio based on the realized yields observed in the market. This two step procedure is applied to the key balance sheet items, which are loans to the non-financial private sector, deposits, securities held and securities issued. These four balance sheet items make up 45% of banks' assets and 53% of liabilities, respectively, see also Figure 1. For the remaining assets, we assume that the appropriate benchmark return is the risk-free rate (measured by the overnight interbank rate). This seems a plausible benchmark as 50% of the residual asset category are claims on the central bank and interbank lending, which is typically done overnight. The remaining part are other assets, such as tangible and intangibles, as well as lending to non-bank financial firms. On the liability side, we also use the risk-free rate as a benchmark return for other deposits, of which 60% are deposits by other banks and central bank liabilities. Finally, we have a residual category of 18% on the liability side which we consider as book equity for the sake of constructing our synthetic bank portfolio. This category consists of capital and other equity instruments (6% of total liabilities), derivatives and short positions (8%) and other financial liabilities not further broken down (4%).

We next describe these two steps in more detail for the different balance sheet positions.

Step 1: extracting risk-exposures from balance sheet information For each bank, we use information about the maturity of banks' position and credit risk exposure in the following way.

For loans to firms, we combine data from AnaCredit and IBSI to achieve the best coverage in terms of maturity and risk (as SUP does not contain information on maturity). AnaCredit data allows for computing cash-equivalent shares (CES), residual maturity and distance to inception by risk category, but only covers the period since 2018 Q3. Therefore, we use IBSI data to backcast the series. In order to breakdown loans to firms by risk categories, we convert the probabilities to default (PDs) available in AnaCredit into risk weights by using the regulatory formula and auxiliary information from supervisory reporting. Then we split loans to firms into three risk categories based on the risk weights (low: up to 20%, medium: over 20% and up to 50%, and high: over 50%). We then compute the relevant measures using the remaining maturity of the loans (based on the interest fixation period for flexible rate loans and

the residual maturity for fixed rate loans) by risk category and original maturity category. The original maturity categories are needed for the back casting. After obtaining the CES, residual maturity and distance to inception, we average these by bank, risk category and original maturity category. We then use the data on original maturity share in IBSI to backcast the series for each risk category (here we have to assume that the distribution of original maturities is the same across risk categories). For banks with no data (not in AnaCredit, not reporting probabilities to default), we assume that the average CES, residual duration and distance to inception per original maturity category is the same as for the other banks in the bank's country. The resulting inputs are plotted in Figures B.1 and B.2 in the Appendix.

For loans to households, we start with information from IBSI on maturity and interest fixation of new loans. While for outstanding loans, only original maturities are available, new loan flows are separated based on their residual maturity or residual fixation. The data is available in three categories: up to 1 year, between 1 and 5 years, over 5 years. In order to get information on residual maturities for outstanding loans, we compute moving sums of the new lending flows. Then the share of each category is computed based on the moving sums and some additional adjustments based on auxiliary data are made.[10] Finally, we need to make some assumptions to arrive at the CES, the residual maturity in months and the distance to inception. For the CES, we assume 70% of loans with residual maturity of up to 1 year are cash-equivalent. This is based on the distribution of residual maturity obtained from AnaCredit, where around 70% of the up to 1 year category, falls below 3 months. To get the average maturity, we apply the following midpoints to each bracket: (1) residual maturity up to 1 year: 8 months; (2) residual maturity 1 to 5 years: 36 months; (3) residual maturity over 5 years: 120 months.

Finally, we also need to compute the average original maturity in months to get the distance to the last interest rate reset/inception of the loan. For this we make the following assumptions about original maturities: (1) original maturity up to 1 year: 8 months; (2) original maturity 1 to 5 years: 48 months; (3) original maturity over 5 years: 180 months. The assumptions are chosen based on information from AnaCredit, such that the resulting averages are similar to the results from AnaCredit for NFCs. Since we do not have similarly detailed data for loans to households, we adjust the assumptions for households to take into account the generally longer maturity of housing loans. The resulting inputs are plotted in Figure B.3 in the Appendix.

For non-financial private sector deposits, we start with five original maturity categories from IBSI

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[10]At the country level, there is information on the share of loans with residual maturity or fixation up to 1 year. This is used to compute an upper bound for the up to 1 year category since there maybe double counting in the new loans aggregation. In addition, a condition is imposed that the share of loans with residual maturity/fixation over 5 years cannot be larger than the share of loans outstanding with original maturity above 5 years, because the latter is a requirement for the former.

(overnight, redeemable at notice with maturity of up to 3 months, redeemable at notice with maturity of more than 3 months, maturity up to 2 years, maturity over to 2 years). To compute the average maturity for the remainder, we assume the following midpoints for each category: (1) redeemable at notice with maturity of more than 3 months: 6 months; (2) maturity up to 2 years: 12 months; (3) maturity over 2 years: 36 months. Finally, we correct for the stability of deposits (see e.g., Drechsler, Savov, and Schnabl, 2021) in two ways. First, we assume that only 50% of deposits with nominal maturity below 3 months are actually cash equivalent. Second, we add 5 years to the nominal average maturity resulting from the calculations described above. In addition, we can obtain the share of deposits which are insured under a national deposit insurance scheme from supervisory data. We use this as a proxy for different riskiness and compute replicating portfolio returns separately for each group. Details on on this are explained in step 2 below.

For securities held and issued, the CES and the average maturity can be computed directly for each bank, as we have security-level information both for the assets and the liability side. In addition, we have information on the rating of each security which we use to split the two portfolios into the same three risk groups as the loans to firms.

Step 2: Benchmark Portfolio Calculation   We use security level data on the yield-to-maturity for euro area sovereign and corporate bonds. This is daily market data which we aggregate up depending on the required input (see below) using nominal values (outstanding amounts).

For loan to firms, we construct the replicating portfolio using the CES and average maturity based on yields of risk-matched euro area sovereign and corporate bonds. Specifically, for the low risk loans, we use bonds rated AAA to AA-, for the medium risk portfolio we use bonds rated A+ to A- and for the high risk portfolio we use bonds rated BBB+ and below (based on the standardised approach for corporate risk weights in the Basel framework, see Article 20.17 here). In terms of timing, we use the yields measured at time $t - x$, where x is the average distance to inception of the loans. And accordingly, use the average maturity $m + x$, where m is the residual maturity discussed before.

For loans to households, we use the yields of sovereign bonds of the country the bank is located in to construct the replicating portfolio. The reason is twofold: first, we have less detailed information on exposures to households. Second, the risk differs from firms (see e.g. the non-performing loans ratio of households vs firms in Figure B.4 in the Appendix), and it is more closely linked to the macroeconomic developments in the country of the borrower. Regarding the timing, we consider as well yields measured at the time of inception of the loans with a maturity equivalent to the current residual maturity

as described above for loans to firms.

For deposits, we separately consider insured and non-insured deposits. However, due to lack of data on maturity by category we apply the same cash-equivalent share and average maturity for both categories. In terms of bond portfolios, we match the insured deposits to sovereign bonds of the country the bank is located in, as the final debtor is the sovereign in this case. And we match the uninsured deposits to the risk category of the bank (based on its credit rating).

For securities, we split the data into three risk bins and construct the replicating portfolio using the CES and average maturity based on yields of risk-matched euro area sovereign and corporate bonds.
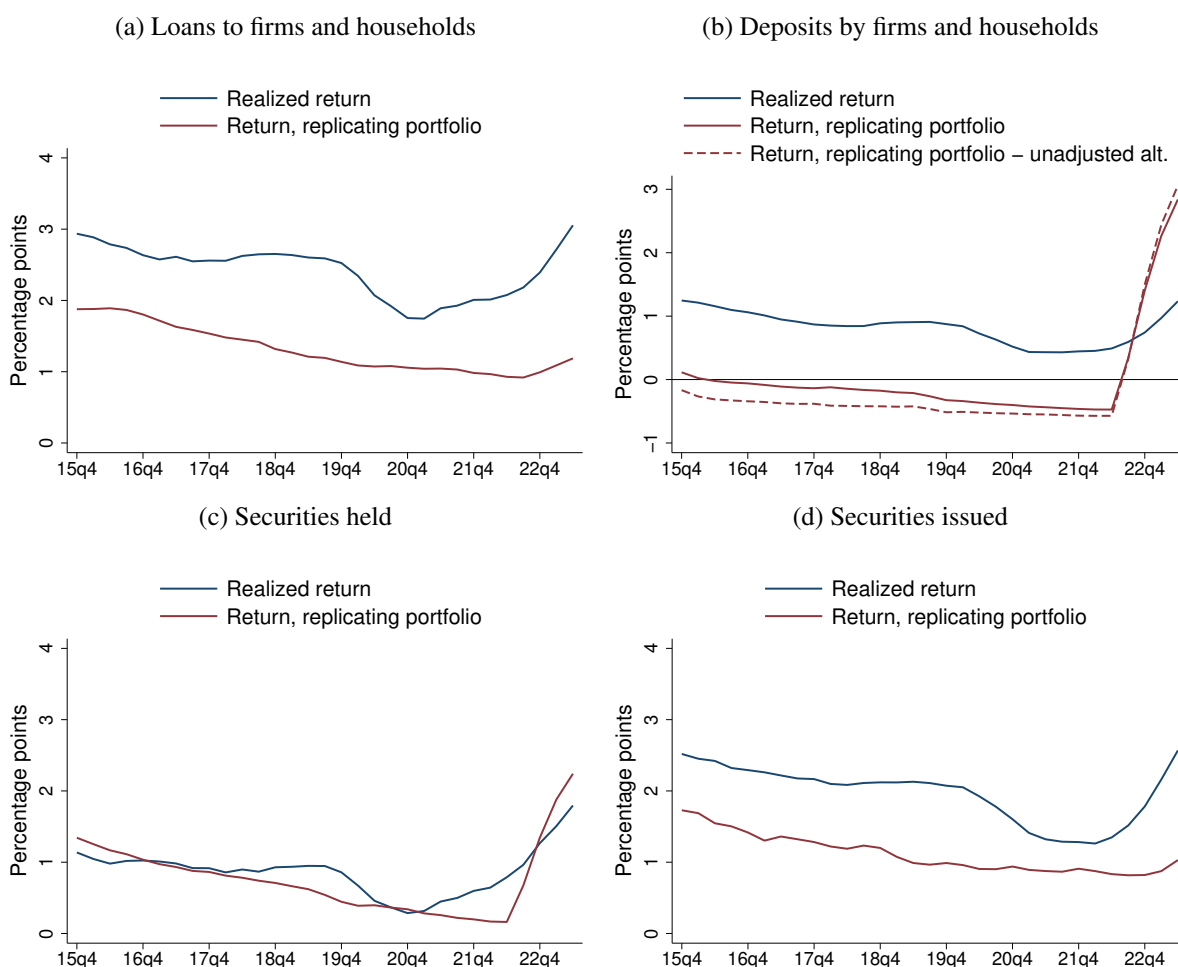
2.3   Calculating the Edge of European Banks

For each bank, we compute the realized returns on each balance sheet item by taking the sum of the net income associated with the respective item in the last four quarters and dividing this by the average outstanding amount in the last five quarters.[11] Operating expenses and non-interest income and expenses are distributed across balance sheet positions based on the latter's share in the total balance sheet. We distribute credit loss provisions on loans and securities according to their relative shares.

Figure 2 shows the realized return for the different balance sheet positions together with the benchmark return from the respective replicating portfolio. The replicating portfolio return for loans to firms and households (see Panel a) is about one percentage point lower on average than the return banks earn on their loans for the most part of the sample until it increases in the wake of the ECB's interest rate hikes (see also Table B.1 in the Appendix). This could be due to unmatched risk-premia (e.g., liquidity risk, as in Bai, Krishnamurthy, and Weymuller (2018), or mark-ups as in Benetton (2021); Benetton, Buchak, and Garcia (2022)). For deposits (Panel b), we see that without maturity adjustment (described above), the benchmark portfolio return was substantially lower than what banks were paying during the period of low or negative policy rates in the euro area. The relationship has reversed substantially since the ECB starting hiking rates. This suggests that the negative gap between replication portfolio and realised returns for deposits before the hiking period was mainly stemming from the distortions associated with the effective lower bound on retail deposits. As the positive interest rate environment was reestablished in July 2022, the liquidity premium on euro area bank deposits increased back to levels comparable to the US (Drechsler, Savov, and Schnabl, 2017). Our replicating portfolio return for securities held mimics

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[11]We use the average of the last five quarters including the present quarter to take into account that the income generated in say the second quarter also relates to assets built up over the second quarter. We choose to annualize returns by summing over income flows of the past four quarters to account for potential seasonality of the income flows recorded in supervisory data according to accounting rules.

Figure 2: **Components of the edge over time, 2015Q4-2023Q2**

(a) Loans to firms and households

(b) Deposits by firms and households

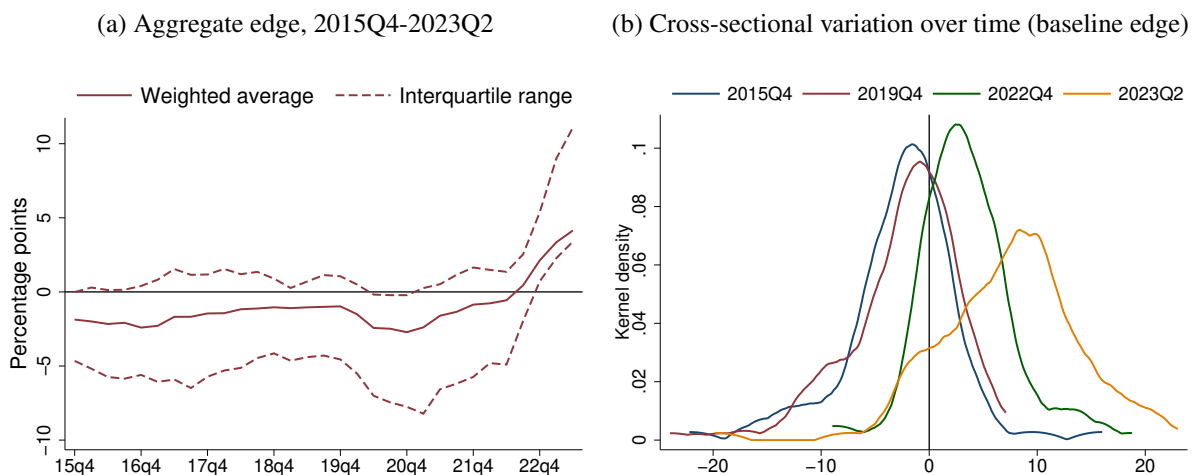

(c) Securities held

(d) Securities issued

Notes: Realized returns are computed by taking the sum of income in the recent four quarters and dividing this by the average of outstanding amounts in the previous 5 quarters. Adjustment for costs distributes operating expenses and non-interest income to each balance sheet item based on its share in the total balance sheet. Replicating portfolio returns estimated using matched bonds based on cash-equivalent shares and average maturity. The unadjusted replicating portfolio return on deposits does not include the adjustment of the CES and average maturity to better reflect the stability of deposits, see Section 2.2.

closely their realized return, indicating that banks pay and earn competitive rates on these securities (see Panel c). Investors in securities issued by banks demand instead a spread of around one percentage point on average compared to other bonds with similar risk and maturity profile (Panel d), consistent with the average bank bond spreads prevailing in the euro area. This could be the reflection of, first, hedging costs when issuing fixed-rate bonds due to banks' preference for floating-rate liabilities. Second, there could be indirect costs associated with underwriting, registration, rating issuance, or legal fees. Third, there may be costs associated with the overcollateralisation of banks' secured funding.

To compute the overall edge for each bank, we first create a synthetic version of the bank's net

Figure 3: **Aggregate edge over time**

(a) Aggregate edge, 2015Q4-2023Q2

(b) Cross-sectional variation over time (baseline edge)

Notes: Edge is difference between realized return and replicating portfolio return. Realized returns are computed by taking the sum of net income in the recent four quarters and dividing this by the average of equity in the previous 5 quarters. Equity is the residual of assets minus securities issued and deposits. Replicating portfolio returns estimated using matched bonds based on cash-equivalent shares and average maturities (adjusted original maturities of outstanding loans in IBSI). Total replicating portfolio return computed as sum of RP cashflows for each balance sheet item over average of equity in the previous 5 quarters.

income by adding the implied income flows from all replicating portfolio positions on the asset side and subtracting the implied cost flows from the replicating portfolio positions on the liability side. Implied cash flows are computed by multiplying the benchmark returns RP_t^i of each balance sheet position with the outstanding amounts of that position (assets A_t^i and liabilities L_t^j). This synthetic income flow is then divided by the average book equity, to obtain the benchmark return on book equity, see last term in equation (1). Finally, we calculate the edge by subtracting the overall benchmark return from the realized return on equity:

$$\text{Edge}_t = \frac{\sum_{k=0}^{3} \text{net income}_{t-k}}{1/5 \sum_{k=0}^{4} \text{book equity}_{t-k}} - \frac{\sum_i A_t^i \times RP_t^i - \sum_j L_t^j \times RP_t^j}{1/5 \sum_{k=0}^{4} \text{book equity}_{t-k}} \tag{1}$$

The edge represents the return on book equity over and above what an investor would have earned for a balance sheet with similar credit and interest rate risks as that of the bank. Figure 3 presents the aggregate edge of banks in the euro area and its cross-sectional standard deviation over time. From 2015Q4 to 2022Q2 (before the ECB started hiking interest rate), banks on average underperformed the benchmark by around 1 percentage points of equity every quarter in annualised terms. Since the second half of 2022 banks' performance relative to the benchmark improved substantially in the context of rapidly increasing policy rates and the exit from accommodative monetary policy, with the average over this period standing at around 2 percentage points. The aggregate average abstracts from large cross-

sectional variation of the edge. We compute negative edges for a substantial fraction of banks in the euro area. The 25th percentile bank had an edge of -4.7 percentage points in 2015Q4 which improved to an overperformance of 3.4 percentage points in 2023Q2. In contrast the 75th percentile bank had an edge of circa 0 percentage points in 2015Q4 which changed to 11 percentage points in 2023Q2.

The shift in the distribution over time is also evident from panel (b) of Figure 3. The sharp increase in interest rates over 2022-2023 led to substantial shifts to the right, in combination with asymmetric effects along the distribution. Notably, banks on the right tail of the distribution experienced a large increase in their edge, while banks on the left tail have become much closer to the average.

3   Drivers of bank performance

Changes to the long term performance of financial intermediaries can result from both structural factors and stabilisation measures. This section investigates the relative strength of potential drivers of bank edges over passive portfolios in a unified framework, isolating the components of bank edges that provide additional information content over alternative measures of bank performance.

3.1   Description of the drivers

Bank edges represent the return banks earn beyond bearing credit and interest rate risk. A large edge could be due to banks' market power in lending markets. More concentrated lending markets allow banks to extract higher unit margins from credit exposures, thus contributing to banks' profitability advantage vis-à-vis other financial investors (see Berger and Hannan, 1989; Petersen and Rajan, 1995). Moreover, the banking sector services credit and deposit needs of firms and households with little competition from other financial intermediaries in the euro area. This comes at the cost of stricter oversight of supervisory authorities on banking business practices compared to other non-bank financial intermediaries. Therefore, higher cost of regulatory requirements to access bank lending and deposit markets may lower bank edges. A high regulatory burden, as proposed by Atkeson et al. (2019), could be a drag on bank performance. Cost inefficiencies may also constitute a relevant determinant of bank edges. The physical and organisational infrastructure necessary to operate the loan and deposit franchises make administrative and personnel costs a much more prominent item in overall operating costs of banks compared to other financial intermediaries. Moreover, banks operate in a highly-regulated sector with a strong presence of governmental authorities among both shareholders and boards, where diverse stakeholders' preferences may stifle cost-minimization efforts.

Monetary policy may also affect bank edges in specific circumstances. While most of the cyclical variation is absorbed by the choice of proper market benchmarks of the portfolio of banks with respect to maturity and risk profiles, the banking sector operates in markets that present different price elasticities and are subject to additional financial constraints compared to other financial investors. This can determine differential responses of performance to monetary policy shocks. For example, the average retail depositor is typically less sophisticated or attentive and hence may react only sluggishly to changes in deposit pricing. Thus, monetary policy tightening may be passed-through more sluggishly to retail deposits than to liabilities of similar maturity and riskiness available to other intermediaries. At the same time, the presence of an effective lower bound (ELB) on the remuneration of retail deposits may constitute a drag on the value of deposits. During times with rates at the ELB, banks' deposit funding advantage is diminished as the operating costs of deposits may dominate the deposit rate interest rate advantage, exerting downward pressure on banks' profitability comparatively more so than on generic investors' portfolios (see, e.g., Altavilla, Boucinha, and Peydró, 2018). Moreover, in light of the larger prominence of banks in financial intermediation in the euro area compared to other jurisdictions like the US, the European Central Bank has often resorted to monetary policy measures specifically targeted to the banking system like funding-for-lending schemes (Targeted Longer-Term Refinancing Operations, TLTROs) in response to disinflationary pressures around the ELB. These measures offered funding terms that were highly advantageous to banks compared to market-based options, especially in the context of the pandemic (see, e.g., Altavilla et al., 2023), and their unwinding presented bank-specific issues as well.

3.2 Measurement of the drivers

All these potential drivers of bank performance are highly endogenous with respect to the bank edges themselves. It is thus key to isolate seemingly exogenous sources of variation in these key determinants. We focus on four different drivers, that is, competition, regulation, cost inefficiency and monetary policy.

First, to measure competition we rely on bank level answers to the ECB's bank lending survey, which asks banks about competition from non-banks. Banks report in each quarter whether over the past three months they have experienced a tightening of credit standards or a decrease in loan demand due to the competition coming non-bank financial intermediaries. Our measure $Com_{b,t}$ thus counts the number of quarters in which banks report such a decrease. This informs us about changes in each bank's perceived market power, and it does so using a source of competitive pressure that does not depend on

each bank's individual pricing policies, market share, or other banks' competitive attitudes. Competition from non-banks traditionally affects directly only mark-ups of banks that offer similar services to non-banks, but technological innovation in the form of digital services and mobile banking have lead to a higher incidence of non-bank competition also in traditional banks' core services like the collection of deposit funding.

Second, to measure each bank's regulatory burden we rely on bank-specific microprudential capital requirements and guidance, $\text{Reg}_{b,t}$, determined in the context of the confidential Supervisory Review and Evaluation Process (SREP) of the SSM, the supervisory arm of the ECB. These individual capital requirements are mostly not public and are therefore a key determinant of supervised banks' pricing policies that is not factored in by market participants. Moreover, while governed by a common framework to ensure a level playing field, they are tailored on an individual basis according to each bank's risk profile. By their very nature, they are forward looking making them have leading indicators vis-à-vis banks' business strategies. At the same time, since these requirements are calibrated to each bank's situation, they are endogenous to pre-existing characteristics. In particular, a bank's risk profile within the SREP is evaluated along four dimensions: business model, governance and risk, capital and liquidity. Most of these characteristics are variations of banks' net worth, which in itself correlates with banks' edge independently of capital requirements. Hence, in most applications below we orthogonalize the capital requirements with respect to direct measures of net worth as follows:

$$\text{Reg}_{b,t} = \beta_0^{\text{Reg}} + \beta_1^{\text{Reg}}\text{Risk weights}_{b,t} + \beta_2^{\text{Reg}}\text{Leverage ratio}_{b,t} + \beta_3^{\text{Reg}}\text{CET1 ratio}_{b,t} + u_{b,t}^{\text{Reg}}, \qquad (2)$$

where $\text{Risk weights}_{b,t}$ are risk weights, $\text{Leverage ratio}_{b,t}$ is the leverage ratio, $\text{CET1 ratio}_{b,t}$ is the CET1 ratio, and β_0^{Reg} is a constant. What is left from this orthogonalization, $u_{b,t}^{\text{Reg}}$, is thus mostly the result of challenges to banks' business strategies, organisational structures, and composition of management bodies.

Third, we measure each bank's cost (in)efficiency as the cost to income ratio, $\text{CIR}_{b,t}$. For most banks, the largest determinant of this ratio is the size of operating expenses, where administrative costs related to personnel and branching are dominant, relative to net interest income. Banks in the euro area, given their often hybrid public-private ownership and management structure, have long suffered of low cost efficiency relative to other financial intermediaries. The large branch network necessary to operate the deposit franchise and to monitor and evaluate the credit-worthiness of potential borrowers, especially in the context of enhanced regulatory and micro-prudential scrutiny, have left the euro area

banking sector's profitability heavily weighed down by operating expenses. Additional frictions coming from labor market rigidity and pension reforms, together with political economy hurdles to M&A's, have further hindered the phase out from a high-operating costs regime for the euro area banking sector. The lack of personnel and managerial mobility have also delayed technological adoption compared to other financial sectors, in particular in the use of mobile banking and integration of business practices with Big Tech services.[12]

Fourth, to measure the impact of monetary policy we rely on high-frequency responses of the Overnight Indexed Swaps around monetary policy announcements, as in Gürkaynak, Sack, and Swanson (2005), Gertler and Karadi (2015), and Hanson and Stein (2015). These high-frequency movements are more likely to reflect the true content of the monetary policy actions taken at each meeting of ECB's Governing Council rather than other confounding factors, and constitute a more exogenous measure of monetary policy shocks that may affect the banking sector, ultimately leading to fluctuations in bank edges. We compute monetary policy shocks, MP_t, as the first principal component of high-frequency surprises at different maturities from ECB monetary policy events identified in Altavilla et al. (2019).

3.3 Empirical set-up to evaluate role of drivers

We investigate how the above determinants affect the edge by using local projection-style regressions à la Jordà (2005) and Ramey (2016).

First, we look at the four determinants mentioned above to observe their relative performance, regardless of the potential interference to identification coming from banks' net worth and unobserved heterogeneity related to macro conditions. The model is as follows:

$$\Delta \text{Edge}_{b,t+h,t-1} = \beta_{1,h}\Delta \text{Com}_{b,t} + \beta_{2,h}\Delta \text{Reg}_{b,t} + \beta_{3,h}\Delta \text{CIR}_{b,t} + \beta_{4,h}\Delta \text{MP}_t$$
$$+ \beta_{5,h}X_{b,t-1} + \mu_b + u_{b,t,h}, \tag{3}$$

where $\Delta \text{Edge}_{b,t+h,t-1}$ is the change in the edge of bank b between quarter $t-1$ and quarter $t+h$ for different horizons h. $\Delta \text{Com}_{b,t}$ takes value 1 is bank b has reported that between $t-1$ and t it faced more competition by non-banks, 0 if it reported no change, and -1 if it reported less competition. $\Delta \text{Reg}_{b,t}$ is the change in capital requirement experienced over the previous quarter, $\Delta \text{CIR}_{b,t}$ is the change in the cost-to-income ratio over the previous quarter, and ΔMP_t is the monetary policy shocks occurred over the previous quarter. μ_b is a bank fixed effect that absorbs bank-specific unobserved heterogeneity. $X_{b,t-1}$

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[12]This reflected onto banks' PtB relative to other financial sectors, as shown in Figure B.5 in appendix.

Figure 4: **Impact of changes in potential determinants of banks' edge**
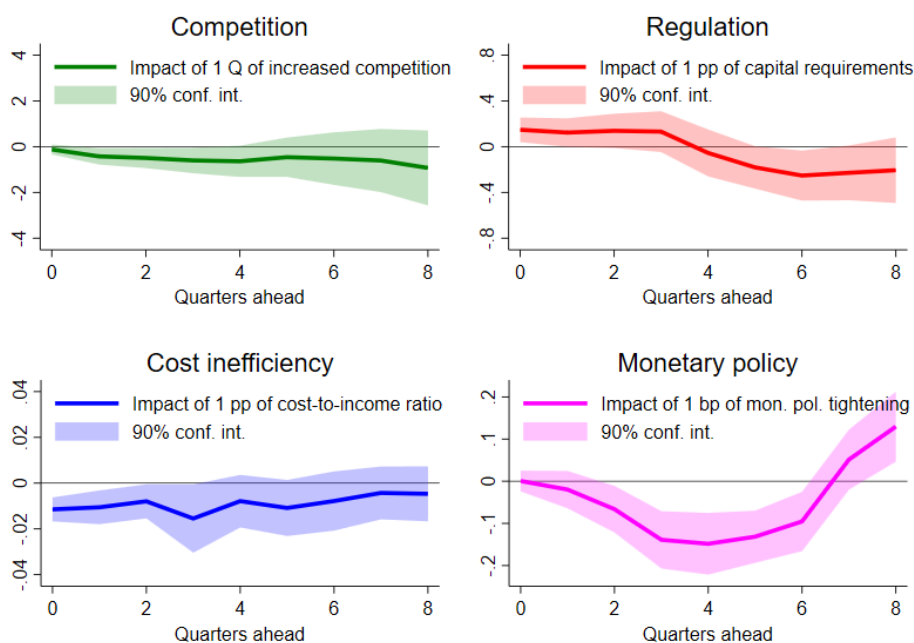
Notes: Charts show the change in the total edge in percentage points for a change in each potential determinant. Dependent variable is in pp, competition in units (1 for a reported increase in competition by non-banks, 0 for no change, -1 for a decrease), regulation (capital requirements) and cost inefficiency (cost-to-income ratio) are in pp, monetary policy (high-frequency reactions around decisions) is in bp. Specification with bank FE, cluster at bank level.

denotes bank level controls relating to bank b's asset composition at $t - 1$, such as the share of excess liquidity (deposits in the ECB deposit facility and central bank reserve holdings in the ECB current account in excess of reserve requirements) in total assets and the share of government bonds holdings in total assets, and liability structure, such as the share of deposits in total liabilities and the share of outstanding targeted longer-term refinancing operations (TLTROs) in liabilities. This set of controls captures a large fraction of the time-varying bank characteristics not directly captured by the bank fixed effects that may characterise banks' business models and exposure to various shocks.

We report the results of the estimation of model (3) in Figure 4. Each panel reports, for each determinant $i = 1, ..., 4$, the estimated coefficients $\hat{\beta}_{i,h}$ for horizons $h = 0, ..., 8$, as well as the associated 90% confidence interval based on standard errors clustered at the bank level. Increased competition in one quarter brings about a decrease in edges of around 0.5 percentage point of equity after 1-3 quarters. An increase of 1 percentage point of capital requirements in terms of risk-weighted assets leads to a temporary increase in edges, which may reflect the potential influence of common determinants of both capital requirements and edges in terms of banks' net worth (see below). A 1 percentage point higher cost-to-income ratio predicts around 1 basis points of lower edge, a difference that is gradually reabsorbed

at longer horizons. Finally, a 1 basis point of monetary policy tightening (easing) leads to a temporary decrease (increase) in the edge of around 10 to 15 basis points at 2-4 quarters ahead, consistent with a faster repricing of bank-based liabilities compared to other securities of comparable maturity and risk profile, followed by a symmetric increase (decrease) at longer horizons.[13]

Figure 5: **Impact of changes in potential determinants of banks' edge orthogonal to net worth**
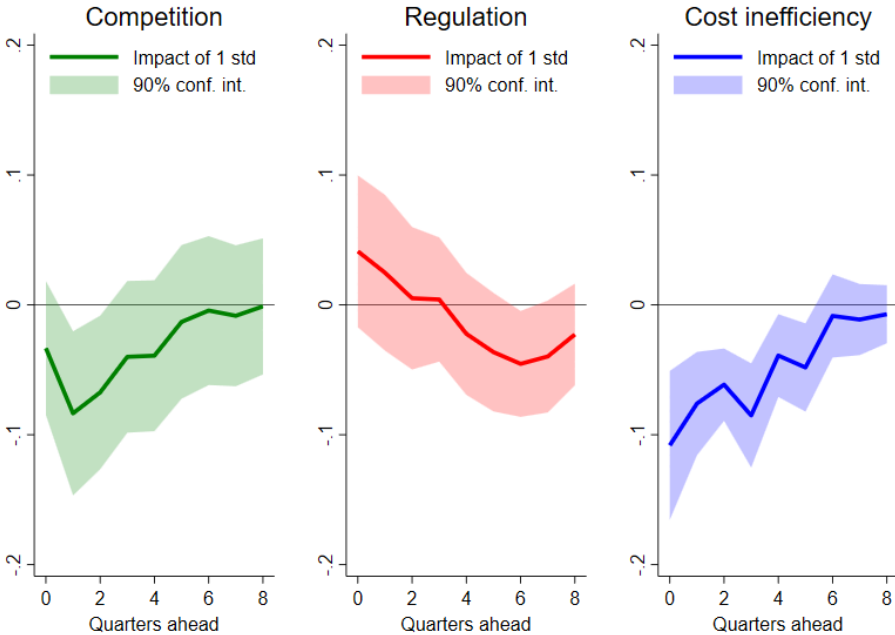
Notes: Charts show the change in total edge associated with the part of a change in each potential determinant that is orthogonal to measures of net worth/riskiness (CET1 ratio, leverage ratio, average risk weight), as estimated in (5). Dependent variable and regressors are standardised. Confidence intervals are based on standard errors clustered at bank level.

Second, we saturate the model in (3) with country-time fixed effects to filter out potential aggregate shocks that may correlate with both determinants and edges. This implies that the monetary policy shocks ΔMP_t are fully absorbed by the fixed effects. Moreover, we control for the fact that part of the edge may simply reflect banks' net worth. What we are interested in is the part of the edge that conveys additional information on top of observable characteristics related to net worth like riskiness, leverage or capitalisation. In model (3), that association is captured by the endogeneity of the regulatory capital requirements, $Reg_{b,t}$. Thus, we orthogonalize the rest of the determinants with respect to measures of net worth by running the following regressions similarly to equation (2):

$$J_{b,t} = \beta_0^J + \beta_1^J \text{Risk weights}_{b,t} + \beta_2^J \text{Leverage Ratio}_{b,t} + \beta_3^J \text{CET1 ratio}_{b,t} + u_{b,t}^J, \tag{4}$$

---

[13]Exploring potential non-linearities in these relations reveals that only monetary policy shocks have a non-linear (concave) impact on bank edges, and only at longer horizons where the overall impact of a hike (cut) is positive (negative).

which yield the parts $\widehat{J}_{b,t}$ of the determinants predicted by net worth and the parts $\widehat{u}_{b,t}^{J}$ unexplained by net worth, for $J = \{\text{Reg}, \text{Com}, \text{CIR}\}$. Then, we take first differences in these variables to estimate a model that decomposes the changes in edges as a function of both the changes in determinants via net worth and the changes in determinants via channels other than net worth, that is,

$$
\begin{aligned}
\Delta\text{Edge}_{b,t+h,t-1} = & \beta_{1,h}\Delta\widehat{\text{Com}}_{b,t} + \beta_{2,h}\Delta\widehat{\text{Reg}}_{b,t} + \beta_{3,h}\Delta\widehat{\text{CIR}}_{b,t} \\
& + \beta_{4,h}\Delta\widehat{u}_{b,t}^{\text{Com}} + \beta_{5,h}\Delta\widehat{u}_{b,t}^{\text{Reg}} + \beta_{6,h}\Delta\widehat{u}_{b,t}^{\text{CIR}} \\
& + \beta_{7,h}X_{b,t} + \mu_{b} + \mu_{c,t,h} + u_{b,t,h},
\end{aligned} \tag{5}
$$

where $\Delta\widehat{J}_{b,t} = \widehat{J}_{b,t} - \widehat{J}_{b,t-1}$ and $\Delta\widehat{u}_{b,t}^{J} = \widehat{u}_{b,t}^{J} - \widehat{u}_{b,t-1}^{J}$, for $J = \{\text{Reg}, \text{Com}, \text{CIR}\}$.

The resulting impacts can be seen in Figure 5. The three panels report the impacts from the residuals $\widehat{u}_{b,t}^{J}$, for $J = \{\text{Reg}, \text{Com}, \text{CIR}\}$. To ease the comparison between panels, we have standardised all variables so as to interpret the coefficients as number of standard deviations of the dependent variable explained by each standard deviation of each regressor.

An exogenous increase in competition that is not associated with changes in net worth/riskiness has a significant negative impact on edges. The impact is economically significant. One standard deviation of higher competition subtracts 8% of a standard deviation in edges at the trough, and the impact is reabsorbed after one year. A similar increase in microprudential pressure prompts no significant impact on bank performance in the short term, but leads to a temporary decline after around 6 quarters which is quickly reabsorbed. Orthogonal changes in cost-to-income ratios instead lead to large and persistent changes in edges. One standard deviation of higher cost-to-income ratio anticipates between 5% and 10% lower edge for one year, which is only partially reabsorbed at the end of the projection horizon. While both competition and cost efficiency are equally impactful at their trough, cost efficiency seems the one with longer-lasting and sizable effects.

Figure B.6 in the Appendix reports also the impact of the part of the determinants predicted by measures of bank net worth. An increase in net worth or riskiness associated with an increase in competition, for instance due to an increase in the size of lending and deposit markets, is not associated with a change in bank edges. An increase in capital requirements prompted by a variation in riskiness or leverage has a negative effect on banks' edge after a few quarters. An increase in the cost-to-income ratio that is associated with net worth and riskiness does not predict any future evolution of edges, most probably reflecting changes in the yield curves that are captured by the proper replicating portfolios.

Figure B.7 in the Appendix explores further the role of the orthogonal cost efficiency in determining

banks' edges, identifying through which item of banks' balance sheets cost efficiency influences the overall edge. While an orthogonal increase in the cost-to-income ratio generates slight deteriorations of the edge across all items, the largest drop is registered in deposits. This suggests that higher cost efficiency in operating the deposit franchise is the key determinant of bank performance vis-à-vis market-based replicating portfolios.

We can also focus on two key cross-sections in our sample, one immediately before the pandemic in December 2019 and another well into the hiking cycle in December 2022, considering the same linear association represented in (5) but in levels, that is,

$$
\begin{aligned}
\text{Edge}_{b,T} = {}& \beta_{1,T}\widehat{\text{Com}}_{b,T} + \beta_{2,T}\widehat{\text{Reg}}_{b,T} + \beta_{3,T}\widehat{\text{CIR}}_{b,T} \\
& + \beta_{4,T}\widehat{u}_{b,T}^{\text{Com}} + \beta_{5,T}\widehat{u}_{b,T}^{\text{Reg}} + \beta_{6,T}\widehat{u}_{b,T}^{\text{CIR}} \\
& + \beta_{7,T}X_{b,T} + \mu_{c,T} + u_{b,T},
\end{aligned}
\tag{6}
$$

where $T = \{2019\ \text{Q4},\ 2022\ \text{Q4}\}$ indicates the cross-section of reference and $\mu_{c,T}$ are country fixed effects. Figure 6 shows that cost efficiency was the main explanatory variable for the cross-sectional differences in edges at the onset of the pandemic, and that neither the pervasive pandemic shock nor the increase in interest rates brought about by the tightening cycle have altered this relation. One standard deviation difference in cost-to-income ratios is associated with around 30% of the standard deviation of banks' edges, whereas the rest of the determinants play no significant role in the cross-section. This is crucial for identification in the following section, as the drop in operating expenses due to the pandemic constitutes an arguably exogenous source of variation in bank edges.

4   Validation of edge as performance measures

The evidence presented in Section 3 shows that the bank edge we measure is correlated with various structural drivers of banks performance, and in particular with the cost-to-income ratio. In this section we proceed to understand whether the edge carries information on banks' intermediation capacity beyond what other performance measures can provide. To this end, we exploit two recent episodes that provided ideal empirical settings where unexpected shocks hit the euro area banking sector. The first is the 2020 pandemic and the second is the financial market turmoil that followed the collapse of Silicon Valley Bank (SVB) and the takeover of Credit Suisse (CS) in March 2023. We use these episodes to gauge to what extent higher edges are a good predictor of i) a lower need to rely on public support in response to shocks

Figure 6: **Relation between potential determinants and banks' edge level**
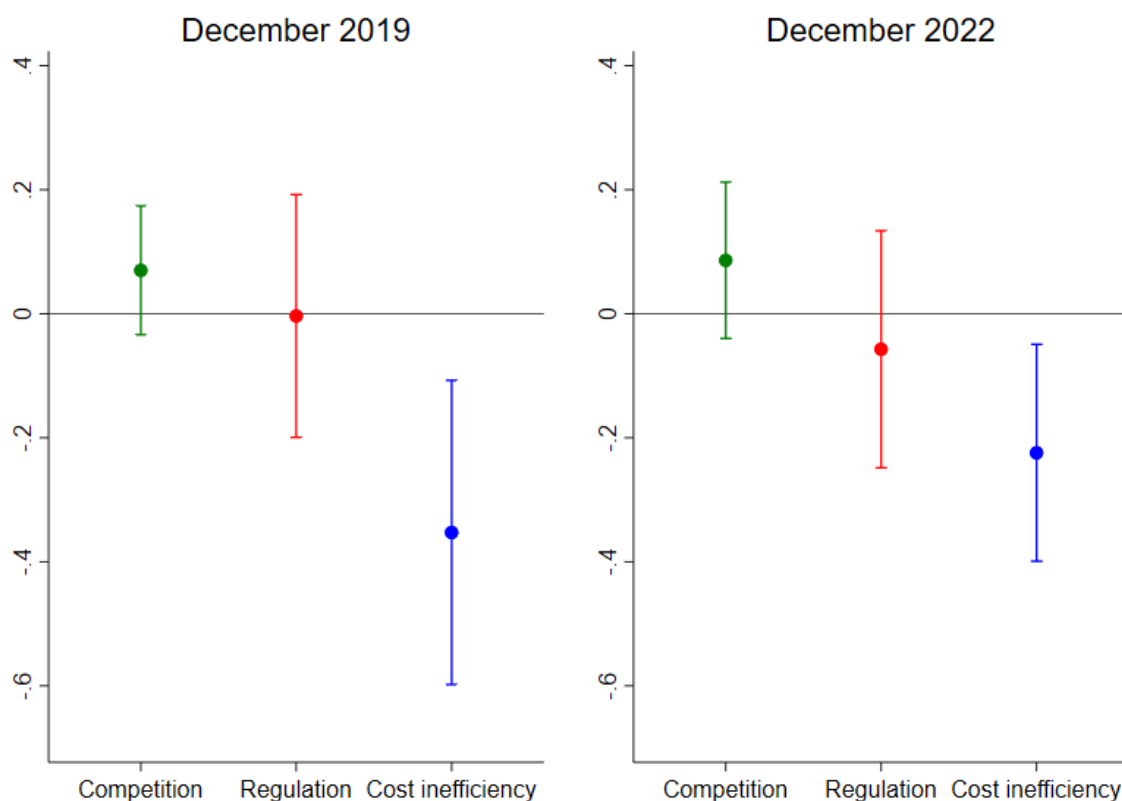
Notes: Charts show the level of total edge relative to 1 std for 1 std of each potential determinant. Dependent variable and regressors are standardised. Each determinant is split between the part predicted by (lagged) measures of net worth/riskiness (CET1 ratio, leverage ratio, average risk weight) and the part orthogonal to these measures. Specification with country FE, robust standard errors.

and ii) a lower or more profitable exposure to interest rate risk and credit risk, especially in comparison with an alternative performance measure like ROE.

4.1 Reliance on public support

We exploit the large shock to bank funding and capital position induced by the outbreak of the Covid-19 pandemic and subsequent containment measures.[14] We show that sorting by the pre-pandemic edge allows us to identify banks which relied particularly strongly on public support measures, in particular loan guarantees. A similar sorting based on more standard profitability measures, such as ROE, does not allow for the same identification. This indicates that the edge is a useful measure to differentiate more vulnerable banks which might be more in need of support.

We measure exposure to the pandemic shock using Google mobility data. This data measures de-

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[14]See Altavilla et al. (2023) for key stylised facts concerning the euro area banking sector during the pandemic.

viations in mobility of Google services' users at a daily frequency at NUTS3-level of geolocational granularity.[15] The deviation is computed with respect to a pre-pandemic 'baseline' mobility pattern. For each location, we compute monthly averages of the percentage deviations from the December 2019 baseline of Google mobility in workplaces. For example, we interpret a monthly average deviation of 100% as the equivalent of a full lockdown implemented in a given location in that month, an average deviation of 50% as the equivalent of half a month of full lockdown or of a full month of partial (50% of potential mobility) lockdown. We then cumulate these deviations over months since December 2019. For example, a cumulated change in monthly averages of workplace mobility by December 2020 of 150% is the equivalent of a month and a half of full lockdowns implemented in a given location between December 2019 and December 2020. In Figure B.8 in the Appendix two panels report, for each location, the cumulated deviations in workplace mobility since December 2019 until December 2020 (left panel) and December 2021 (right panel). The figure shows the large cross-sectional heterogeneity generated by the staggered spread of the virus and adoption of containment measures.

In terms of public support we focus on the public loan guarantee schemes. Following the outbreak of the Covid-19 pandemic, most European governments introduced guarantee schemes to support bank lending to the private sector.[16] Banks could receive guarantees covering up to 100% (and at least 70% in most cases) of loans to firms. The intention was to support the flow of credit to the real economy, in particular to small and medium sized companies and those most affected by the lockdown policies at a time of unprecedented economic slowdown. To this end, the guaranteed amount was larger for smaller companies in most countries, and only firms which did not face financial difficulties before the pandemic were eligible to receive guaranteed loans. In addition, several programs included limits on the interest rates banks could charge on these loans. Due to their attractive conditions the programs were heavily used and large fractions of newly issued loans in 2020, in particular the first half of the year, were covered by these government guarantees. We focus on this particular support measure as it was accessible to a similar degree to all banks in our sample and the strong demand for loans in the early stages of the pandemic implied that most banks were also facing demand for these loans. Therefore, variation in the exposure to the guarantees across banks is more likely to reflect the degree to which banks (and their borrowers) required this support. In contrast, other support measures such as the ECB

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[15]The disaggregation at NUTS3 level is available for most countries. Data for Belgium is available only at NUTS2, data for Germany at NUTS1, and data for Malta and Luxembourg at NUTS0.

[16]For an overview of the programs in the largest four euro area countries, see, e.g., Altavilla et al. (2021c), Falagiarda, Prapiestis, and Rancoita (2020) and Anderson, Papadia, and Véron (2021). In addition, the European Banking Authority provides a detailed overview of all programs in the European Union on its website, which covers programs by 18 of the 19 euro area countries.

targeted longer-term refinancing operations (TLTROs) and prudential measures were also dependent on other characteristics of the banks (such as their remaining borrowing allowance under the ECB TLTRO lending scheme or the banks' pre-pandemic capital buffers, see below for more on these measures).

We measure the degree to which banks resorted to guaranteed loans as the change in the percentage of outstanding loans covered by public guarantees since December 2019. We use confidential supervisory data collected for the specific purpose of monitoring banks' exposure to the Covid-19 shock and access to public support measures. By the end of 2020, 3% of outstanding loans were covered by guarantees on average in our sample, with the 75th percentile at 5%, despite the programs only running for less than a year by then. These loans provided support for banks, as they allowed lending with limited capital impact at a time of high uncertainty and high demand for liquidity by the private sector.[17]

Panel (a) of Figure 7 shows that banks more intensely exposed to the pandemic shock have also resorted more to public support in the form of guaranteed loans. We compute exposure of banks to the lockdowns as weighted averages of cumulated deviations in workplace mobility across locations in which each bank is present, where weights are outstanding loans of each bank in a given location at each point in time. For each quintile of exposure to the lockdowns during the pandemic we compute the average level of banks' reliance on guaranteed loans, distinguishing between banks with positive and negative edges in December 2019. We find that larger exposure to the lockdowns leads to higher resort to the policy support measures. Yet, banks with positive edges at the onset of the pandemic did not rely as much public support as other banks. This shows that the edge provides information on which banks are particularly vulnerable and thus required more support. Importantly, this information does not appear to be conveyed in a similar fashion by other measures of bank performance. In particular, when splitting banks by a pre-pandemic, backward-looking measure of profitability (specifically via ROE, splitting at the 50th percentile, which is equivalent to the split into positive/negative edge), we find no difference across the two groups of banks (panel (c) of Figure 7). In addition, the differentiation between the banks due to their edge reflects information contained in the edge that is also not related to net worth. As we have seen above, net worth is a potential confounding variable. We therefore also check whether the edge cleaned of the parts related to net worth contains information on the public support reliance. Panel (b) of Figure 7 shows that indeed the part unrelated to net worth is the main driver of the difference between positive and negative edge banks. If we perform a similar check for ROE, we find again almost no difference between the two groups (panel (d) of Figure 7).

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[17]Due to the public guarantee the riskiness of the loans for risk provisioning and capital allocation was largely linked to the sovereign risk which is significantly smaller than firms' riskiness.

Figure 7: **Reliance on policy support by banks' edge**
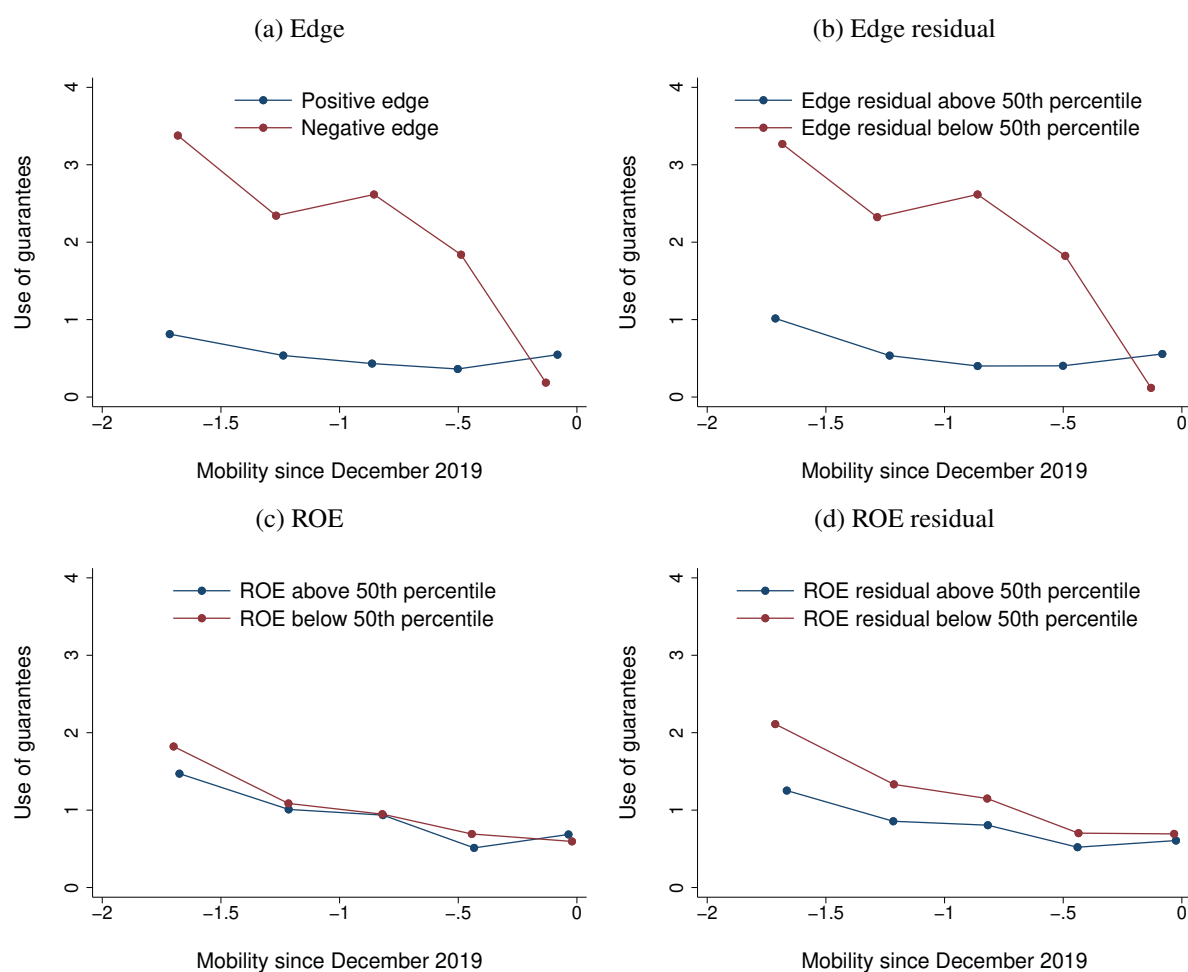
(a) Edge

(b) Edge residual

(c) ROE

(d) ROE residual

Notes: Data split into 5 bins for banks with positive edge/value above the 50th percentile (blue) or negative edge/value below the 50th percentile (red) in December 2019. Y-axis reports changes (in percentage points), with respect to level in December 2019, of the share of loans with Covid-19 related government guarantees in total loans until June 2021. X-axis reports deviations in mobility in workplaces (as a percentage of pre-pandemic mobility) cumulated since December 2019. It is measured in number of months of complete lack of mobility since December 2019, with negative numbers indicating a decrease in mobility (-1 means a decrease of mobility equivalent to 1 month of complete lack of mobility). Exposure of banks is based on weighted averages of cumulated deviations in workplace mobility across locations in which each bank is present, where weights are outstanding loans of each bank in a given location at each point in time. Residuals result from bank-level regressions of the edge/ROE on the CET1 capital ratio, the leverage ratio and the average risk weights.

In Figure B.9 in the Appendix we consider two additional policy measures which were relevant during the pandemic: unconventional monetary policy in the form of the ECB's TLTROs and macropru-dential and microprudential measures which reduced banks' capital requirements. Regarding TLTROs, we compare the change in take-up as a percentage of borrowing allowance since December 2019 across the two groups of banks.[18] Consistent with what we find for government guarantees, we find that banks

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[18]TLTROs are part of the monetary policy instruments put in place by the ECB since 2014. Via these programs the ECB provides longer term funding (at typically three or four years maturity) with an incentive structure that supports lending to the private sector. At the onset of the pandemic the ECB recalibrated the third series of TLTROs (TLTRO III), which had been

more exposed to the pandemic relied more on TLTROs, that the reliance was more pronounced for banks with a negative edge, and that the difference between positive and negative edge banks is mainly due to the part of the edge not related to net worth (left charts in panels (a) and (b) of Figure B.9). To capture prudential measures, we consider the change in individual banks' capital requirements due to measures adopted by the relevant authorities in the first half of 2020.[19] For this policy, there is almost no distinction across banks depending on their exposure to lockdowns, which is plausible as the measure was extended by micro- and macro-prudential authorities directly and did not rely on banks' applying for the support.

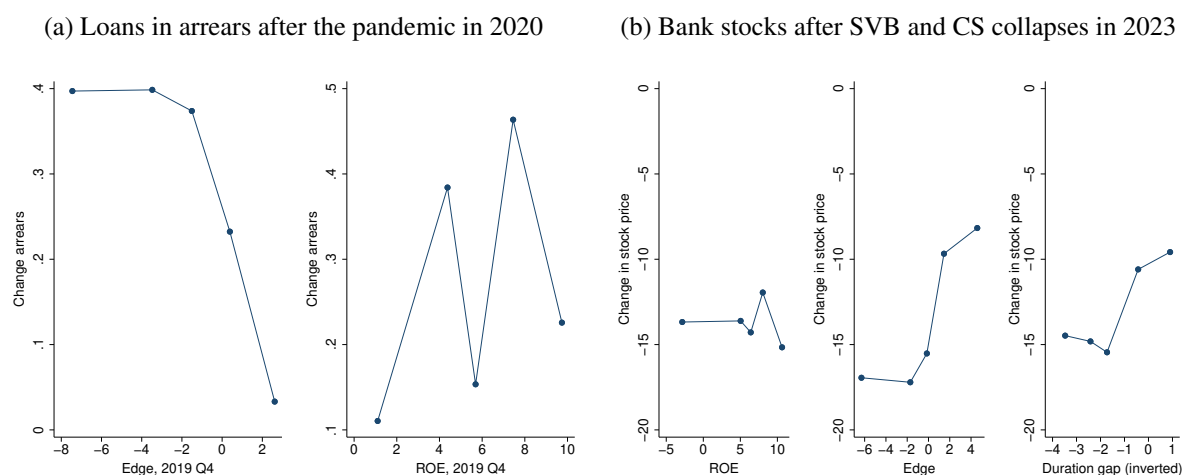## 4.2 Exposure to interest rate risk and credit risk

Banks may achieve higher profitability via higher risk taking, for instance thanks to higher interest rate risk exposure or higher credit risk exposure. At the same time, higher exposures also make more profitable banks more susceptible to shocks that let these risks materialise. This is the case for measures that ignore the exposure to credit risk and interest rate risk, like ROE. Bank edges instead filter out systematic differences in profitability associated with with these aspects, offering therefore a measure of bank performance that complements the information provided by more traditional measures.

Figure 8 shows that banks with a higher edge are less likely see a significant decline in their intermediation capacity in response to a shock. For instance, Panel (a) shows that banks with higher edge experienced a much lower increase in loan arrears after the outbreak of the Covid-19 pandemic. Instead, banks with a higher ex-ante ROE were not systematically associated with an ex-post different accumulation of arrears. This would suggest that bank edges better capture banks' ability to achieve a good performance that is resilient to the manifestation of adverse shocks. Panel (b) takes instead another episode, i.e., the financial market turmoil that followed the unexpected collapse of SVB and CS. These bank troubles in the US and in Switzerland had global spillovers on bank equity valuations, including those of euro area banks. The latter lost between 10% and 15% of their market value on average in the days immediately after the SVB and CS collapses. Part of these temporary market corrections were also associated with investors' perception that the large interest rate risk exposures that had originated the

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running since September 2019, introducing more attractive conditions for banks. In particular, for a limited period of initially one year (later extended to two years), banks would pay an interest rate as low as -1% if they managed to achieve certain lending targets. In combination with the high demand for liquidity by the private sector, this led to an increased uptake of the program in particular in 2020 (see Altavilla et al. (2023) for details and an assessment of the impact on bank lending during the pandemic). The borrowing allowance of TLTRO depends on the size of the loan portfolio of the banks and was also increased with the recalibration in early 2020, providing additional scope for borrowing by banks.

[19]In response to the pandemic shock, the ECB and the relevant national authorities released macroprudential capital buffers, which had been build up before the crisis, and introduced several microprudential measures, such as allowing banks to operate below certain capital requirements without sanctions (see e.g., Altavilla et al. (2023) for a discussion of these measures and their impact).

Figure 8: **Exposure to credit risk and interest rate risk**

(a) Loans in arrears after the pandemic in 2020   (b) Bank stocks after SVB and CS collapses in 2023

Notes: Data split into 5 bins for quintiles of ROE, edge and (inverted) duration gap (the difference between the weighted average residual maturities for loans, deposits and securities as they enter the computation of the edge) of euro area banks, indicated on the horizontal axes. ROE, edge and duration are all measured in 2019Q4. In Panel a, the variable on the vertical axes is the change in the average share of arrears over total loans at the bank level between 2019 Q4 and 2021 Q4. In Panel b, the variable on the vertical axes is the change in stock prices of euro area banks between 9 March 2023 and 20 March 2023, i.e., from just before the collapse of Silicon Valley Bank and right after the announcement of the merger between Credit Suisse and UBS.

collapses in the US and Switzerland (once paired with liquidity risk) could have been conducive of similar issues also in the euro area. The LHS chart of Panel (b) shows that, from the standpoint of ROE, euro area banks were indistinguishable from each other. Instead, the mid chart shows that a higher ex-ante edge was indeed associated with a lower market correction. Note that for this representation we chose to use bank edges from before the pandemic, to align with Panel (a) and to show how long-lasting the unique information contained in bank edges can be.[20] This higher ability of edges to predict performance even in presence of severe shocks can be due to either a lower exposure to credit risk and interest rate risk, or to a similar level of exposure than other banks that is however more profitable. The right-most chart of Panel (b) finds that the change in stock market valuations after the shock was associated with a higher duration gap between assets and liabilities in banks' balance sheets. In other words, it shows that, at least for the specific case of the March 2023 financial market turmoil, bank edges really anticipated banks' higher resilience to the manifestation of interest rate risk.

In the following section we show that this higher resilience to shocks also translated into more credit to firms when the pandemic shock hit. Moreover, a higher bank performance was associated with more credit directed to more productive firms, which also supported firm investment rates throughout the

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[20]The equivalent panel repeated with edges just before the shock, i.e., in 2022Q4, yields a very similar message.

pandemic downturn.

5 Real effects of bank edges

In the previous section we showed how bank edges identify structural components of bank performance that are not related to bank maturity transformation or risk taking and that are not just a reflection of their measurable net worth and riskiness. In this section we take a step further to show what information these bank edges contain regarding banks' intermediation capacity and resilience to the manifestation of risk. To do so, we exploit the variation of bank edges to explain the evolution bank lending volumes to firms and, eventually, firms' investment behaviour during the pandemic.

5.1 Bank edges and bank loan supply

More profitable banks are in a better position to intermediate monetary policy and their ability to be ultimate providers of credit to the real economy is more resilient to shocks than that of struggling banks. Thus, we want to determine whether our measure of performance is indeed associated with a higher propensity to lend by banks. To do so, we make use of euro area credit register (AnaCredit), discussed in Section 2.1 to isolate supply and demand components in the corporate lending market, and explore the role of bank edges as shifters of loan supply.

Casting a causal link between exposure to bank edges and lending volumes requires identifying the dominant transmission channel of edges and to disentangle it from all the confounding factors. With this in mind, our identification strategy relies on a standard set-up exploiting the variation in edges at the bank level while absorbing most of the confounders at the firm level, and in particular loan demand components, by saturating the model with firm-time fixed effects (Khwaja and Mian, 2008). By relying on firms with more than one lender, differences in loan volumes from different lenders for the same borrower can be interpreted as the result of differences in the edges of the lenders, once a rich set of time-varying controls at the bank level is included in the specification.

The main challenge to identification comes, however, from the fact that bank edges may be endogenously related to unobservable characteristics that influence banks' ability to extend credit.

Column 1 in Table 1 reports an exercise that addresses the potential endogeneity of the bank edge with an instrumental variable (IV) strategy, where the bank edge is instrumented by cost inefficiency in a first stage and the component of bank edge predicted by cost inefficiency is used as a regressor for loan volumes in a second stage. Ten percentage points of lower cost-to-income ratio (in our regression sample,

one standard deviation corresponds to 15 percentage points cost-to-income) translate into 1 percentage point of higher edge (in our regression sample one standard deviation corresponds to 5 percentage points of edges), which implies an increase in loan volumes of around 3%.[21]

In Section 3 we show that cost inefficiency is a significant determinant of bank edges. Yet, we also show that other determinants related to competition and regulation play a role. Hence, there may be variation in the bank edges determined by these alternative determinants that plays a role in the impact that bank edges have on bank credit supply. In columns 2 to 4 of Table 1, we use the control function approach (CFA) proposed by Train (2009) to address this additional potential endogeneity. This method consists of two steps. In the first stage the edge is regressed on the same set of variables that are used in the loan volume regression plus our preferred determinant of banks' edges, that is, cost efficiency, which we use as instrument. In the second stage, we regress loan volumes on both the edges, the controls used in the first stage, and the residuals of the first stage regression. The residuals from the first stage capture the variation in edges that is not explained by observables and the instrumental variable, and are therefore supposed to cover any unobservable confounding factor that affects both edges and loan volumes, see also Wooldridge (2015) and Ioannidou, Pavanini, and Peng (2022). The first stage of the CFA is thus

$$\text{Edge}_{b,t} = \beta_1 \widehat{u}_{b,t}^{\text{Com}} + \beta_2 \widehat{u}_{b,t}^{\text{Reg}} + \beta_3 \widehat{u}_{b,t}^{\text{CIR}} + \beta_4 X_{b,t} + \varepsilon_{b,t}, \tag{7}$$

and the second stage is

$$\text{Loan volume}_{b,f,t} = \gamma_1 \text{Edge}_{b,t} + \gamma_2 \widehat{\varepsilon}_{b,t} + \gamma_3 \widehat{u}_{b,t}^{\text{Com}} + \gamma_4 \widehat{u}_{b,t}^{\text{Reg}} + \gamma_5 X_{b,t} + \mu_{f,t} + u_{b,f,t}, \tag{8}$$

where $\mu_{f,t}$ are firm-time fixed effects, $\widehat{\varepsilon}_{b,t}$ controls for the endogenous component of the relation of edges with loan volumes, and $X_{b,t}$ are bank-level control variables as used in the determinants regression as well (see Section 3).

Columns 2 to 4 of Table 1 report the results of the second stage (the first stage is basically just the analysis in Section 3). The empirical strategy allows us to split the correlation between edges and loan volumes into two parts, a still endogenous part collecting the impact of the common unobservable determinants of both edges and loan volumes, represented by the residual of the first stage, and a part orthogonal to these confounding factors, pinned down by the variation in cost efficiency. Increases in cost efficiency lead to higher edges which translate into higher lending volumes, with a magnitude similar to

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[21]Just as an order of magnitude of the aggregate impact during the pandemic, the drop in banks' operating expenses between end-2019 and the first half of 2020 brought about around 1 percentage point improvement in ROE of euro area banks.

Table 1: **Impact of edge on banks' lending conditions**

Dependent variable:	(1) Loan volume	(2) Loan volume	(3) Loan volume	(4) Loan volume	(5) Loan volume
Bank edge	0.032**	0.036*	0.022*	0.022*	0.027**
	(0.016)	(0.019)	(0.011)	(0.011)	(0.011)
Endogenous component $\hat{\varepsilon}_{b,t}$		-0.037*	-0.022**	-0.023**	-0.024**
		(0.021)	(0.010)	(0.010)	(0.010)
Bank ROE					-0.003
					(0.004)
Firm-time FE	YES	YES	YES	YES	YES
Bank controls	NO	NO	YES	YES	YES
Bank net worth var.	NO	NO	NO	YES	YES
Other edge determ.	NO	NO	NO	YES	YES
Model	IV	CFA	CFA	CFA	CFA
Observations	16,698,211	16,698,211	16,698,211	16,698,211	16,698,211
Adj. R-squared		0.43	0.43	0.43	0.43

Notes: Standard errors clustered at the bank level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the IV results of column 1.

To further refine the identification, we also include time-varying bank controls capturing key balance sheet characteristics associated with business models and exposure to monetary policy shocks in the CFA model, see Column 3. The resulting coefficients are similar to the simpler specification. In Column 4 we introduce also the measures of bank net worth used in (6) as well as the rest of the determinants of bank edges orthogonalised by the net worth and riskiness, substituting our cost efficiency measure with its orthogonalised version. The impact of bank edge on lending conditions stands at around 2% of loan volumes for each percentage point of bank edge.

Finally, in Column 5 we include banks' ROE as a more traditional measure of bank performance. While the impact of the edge on loan supply remains significant, ROE has no impact of loan supply. This confirms our result from Section 4 that the edge provides unique information about banks, beyond standard measures of bank profitability. Table B.4 in the appendix shows additional robustness on this horse-race specification.

Table 1 shows a positive impact that a higher edge has on bank credit supply while Section 4.2 shows that banks with a higher edge are also more resilient to the materialisation of interest rate risk and credit risk. We illustrate in Table 2 the mechanism through which this realises, at least for the loan book.

We make use of data from Bureau Van Dijk's Orbis, which provides financial information for listed

Table 2: **Impact of edge on banks' lending conditions – depending on firm characteristics**

| | Dependent variable: loan volume | | | |
| | (1) | (2) | (3) | (4) |
Sample split based on:	Firm ROA	Firm leverage	Firm productivity	Zombie indicator
Below threshold				
Bank edge	0.018**	0.022**	0.013	0.020**
	(0.009)	(0.010)	(0.008)	(0.009)
Above threshold				
Bank edge	0.022**	0.017*	0.026**	0.025***
	(0.010)	(0.009)	(0.010)	(0.009)
F-test: Below threshold = Above threshold				
Edge	0.425	0.320	0.066*	0.529
Firm-time FE	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES
Model	CFA	CFA	CFA	CFA
Observations	4,407,516	4,407,516	4,407,516	4,407,516
R^2	0.38	0.38	0.38	0.38

Notes: Firm leverage is measured as the ratio of debt over assets. Firm productivity is measures as the ratio of firm sales over firm employment. Zombie indicator is a variable that takes value 1 if a firm is classified as a zombie firm and zero otherwise. The threshold used to split the sample into two groups is the median value for the continuous variables in Columns 1 to 3 and the value of 1 vs 0 for the zombie indicator variable in Column 4. Standard errors clustered at the bank level are reported in parentheses. For F-tests, p-value is reported. *** p<0.01, ** p<0.05, * p<0.1.

and unlisted firms worldwide at a yearly frequency.[22] We match firms in Orbis with euro area banks via their exposures reported in AnaCredit, which covers close to the universe of bank exposures to companies. The resulting sample of around 200,000 firms is distributed across 12 euro area countries between 2018 and 2021.[23]

We then run the same specification within subsamples of firms above and below a certain threshold value of firm observables. Column 1 and Column 2 show that banks that increase credit because of their higher edges do so by extending more credit across the board, with no significant differences between firms with a higher or lower ROA, or higher and lower leverage. While the coefficients are slightly tilted towards stronger lending to more profitable and less leveraged firms, the differences are not statistically significant according to F-tests. Instead, Column 3 shows that higher edge banks extend more credit to more productive firms. Finally, in Column 4 we find no evidence of significantly higher zombie lending

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[22]See Giannetti and Ongena (2012) and Kalemli-Özcan et al. (2024) for an overview of Orbis firm-level information.

[23]The list of countries includes Austria, Belgium, Germany, Greece, Spain, Finland, France, Italy, The Netherlands, Portugal, Slovenia, and Slovakia.

for banks with higher edges.[24]

5.2 Real effects of edges via bank loan supply

We showed the crucial role played by bank edges in fostering bank credit supply and in strengthening the resilience of the euro area banking system with respect to the pandemic shock. In this sections we take a look further down in the transmission mechanism to understand whether the increased bank lending supply due to improved bank edges at the onset of the pandemic had also an impact on the real economy. In particular, we look at whether firms more exposed to banks with higher edges could sustain larger investment rates over the pandemic.

For each firm in Orbis we compute the weighted average of bank characteristics using pre-existing credit exposures of each bank to each firm as weights. We assume that firms connected with intermediaries with a higher edge are more exposed to them. Table B.3 summarizes the main variables of the firm-level dataset for the benchmark regression sample, that is, the cross-section of firms in 2019 for which the dependent variables include the change over the pandemic and the potential impact of the bank edges.

Our identification strategy for the real effects of edges during the pandemic relies on three elements. First, we exploit the cross-sectional variation in bank edges as of March 2020. The forced closure of bank branches at the onset of the pandemic induced a large drop in banks' operating expenses, equivalent to 1 percentage point out of a total pre-pandemic ROE of over 5% (see Figure B.10 in the Appendix). During the pandemic, euro area banks' ROE decreased to 2% mostly due to bank provisions, and would have been 1% if operating expenses had not dropped. This sizable positive contribution to bank profitability was specific to banks compared to the replicating portfolios that do not feature operating expenses, which implies that edges were exogenously propped up at the beginning of the pandemic from the increase in cost efficiency. Isolating the component of cost efficiency not explained by bank net worth further strengthens the interpretation. Second, we isolate the bank credit supply channel via the panel estimation in (8), focusing on the predicted loan volumes in the cross-section of March 2020, $\widehat{\text{Loan volume}}_{b,f,\text{March 2020}}$. The presence of firm fixed effects allows to exploit the variation across banks for the same borrower to absorb the component of loan volumes related to loan demand, and the control function approach controls for potential residual endogeneity of edges with respect to loan volumes.

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[24]Our benchmark definition of zombie is a firm with an interest coverage ratio that is less than 1 for three consecutive years and that is active in the market for at least 10 years (Adalet McGowan, Andrews, and Millot 2018). Employing alternative definitions of zombie firms does not change the result.

Third, we use the predicted loan supply based on the estimation in equation (8) to explain investment ΔI_f at the firm level between 2019 and 2020. We estimate the following model:

$$\Delta I_f = \beta_1 \widehat{\text{Loan volume}}_f + \beta_2 X_{b(f)} + \beta_3 X_f + \mu_{\text{ILS}} + u_f, \tag{9}$$

where the observation is a given firm f. $\widehat{\text{Loan volume}}_f$ is the predicted loan supply in March 2020 ($\widehat{\text{Loan volume}}_{b,f,\text{March 2020}}$) from model (8) aggregated for each firm f,

$$\widehat{\text{Loan volume}}_f = \sum_b w_{b,f} \widehat{\text{Loan volume}}_{b,f,\text{March 2020}}, \tag{10}$$

where $w_{b,f}$ is a weight equal to the outstanding loan volume between bank b and firm f in February 2020. $X_{b(f)}$ are the same bank-level controls included in (3) and (8), aggregated at the firm level in the same way as $\widehat{\text{Loan volume}}_{b,f,\text{March 2020}}$. X_f are firm-level observables in 2019, including the size in terms of assets, the return on assets, sales per worker, the leverage ratio and the share of liquid assets. Finally, μ_{ILS} are industry-location-size (ILS) fixed effects controlling for the firm's sector, location and size. These fixed effects allow to absorb the variation in investment across firms that reflect unobserved characteristics of the firm related to, e.g., the evolution of the macroeconomic outlook in a given country, and differences regarding the impact of Covid-19 across sectors and firm sizes. In this way, the only variation left is the differential exposure at the firm level to the pandemic-induced increase in cost efficiency-related edges.

Column 1 of Table 3 shows the results of the benchmark specification, focusing on the growth in investment between 2019 and 2020. One percentage point of higher loan supply at the onset of the pandemic due to a higher bank edge translates into 3 percentage points of higher investment one year into the pandemic. Considering the increase in loan supply of around 3% calculated in Section 5.1, an improvement in bank edges by 1pp due to the pandemic-induced cost efficiency gains could have staved off an economically sizeable decline in investment one year later of around 9 percentage points or 30% of the standard deviation of investment growth.

In column 1 we rely on ILS fixed effects to control for effects common across industries, locations and sizes (given our single period sample). In column 2 of Table 3 instead we include the previous year which allows us to use firm fixed effects alongside country-year fixed effects. The resulting effect is similar to the cross-sectional regression, with a 1 pp increase in predicted loan volumes increasing the investment growth by around 4 pp.

Finally, the various "placebo" specifications columns 3 to 5 confirm that our results do not just pick up

Table 3: **Impact of edge on firms' investment**

Dependent variable:	(1) Investment growth, 2020	(2) Investment growth, 2020	(3) Investment growth, 2019 (placebo)	(4) Investment growth, 2020	(5) Investment growth, 2020
Banks' loan volume (predicted)	2.95** (1.29)		-1.68 (2.04)		
Banks' loan volume (predicted) x (I=2020)		4.50** (1.89)			
Banks' loan volume (predicted), 2019				1.49 (1.40)	
Banks' loan volume (predicted), 2021					6.24 (3.84)
Sample	Cross-section	Panel	Cross-section	Cross-section	Cross-section
Bank controls	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES
ILS FE	YES	NO	YES	YES	YES
Firm FE	NO	YES	NO	NO	NO
Country x Year FE	NO	YES	NO	NO	NO
Observations	181,934	332,978	179,504	147,143	2,736
R-squared	0.05	0.31	0.02	0.05	0.04

Notes: Standard errors clustered at the main bank level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

spurious correlations. In column 3 we use investment growth over 2019 instead of 2020 as the dependent variable and find no significant effect of our variable of interest. In columns 4 and 5, we instead use loan growth from alternative periods, again finding no significant effects on investment growth in 2020.

While our main focus in this section is the impact on firm investment, we also consider the effect on other firm outcomes, see Table B.5. First, the increase in investment appears to be related to tangible investments (columns 1 and 2). Second, the increase in investment also increases the total balance sheet of firms and their total loans, i.e., firms did not simply substitute other funding with loans, and they increased in size with the investments. Third, firms which saw higher credit supply linked to the higher edge of their banks during the pandemic also increased employment relatively more during this period. At the same time, the impact on firm sales was positive, but not significant. Fourth, firm profitability was not significantly affected, and firms did not see a significant change in either their total interest paid or their EBITDA to interest ratios. Finally, increased lending from higher edge banks during the pandemic did not reflect into an increased likelihood of a firm being classified as zombie.

6   Conclusion

In this paper, we use granular confidential data to construct a measure of bank performance that complements the information provided by existing metrics. The measure, which reflects a bank's edge over a market-based and risk-matched benchmark portfolio, is mainly explained by structural factors, such as higher bank cost efficiency and, to a lesser extent, competition by non-banks. Stabilisation policies, such as monetary measures, and tighter regulation, like capital requirements, instead have a more muted role in explaining the performance of the banking sector. We validate our measure by showing that high-performance banks, i.e., banks with higher edge, are relatively more resilient to shocks (such as Covid-19 or the financial market turmoil in March 2023) and therefore need less reliance on public measures. Moreover, we show that banks with higher edges are able to provide more credit to firms, directing it to more productive firms, and that firms more exposed to higher edge banks sustain higher investment rates.

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A Data

Our dataset is compiled by merging various micro (bank-level, instrument-level or firm-level) datasets. The merging is done using unique identifiers and taking into account corporate structures.

ECB's Supervisory Reporting data The dataset defining our core sample, which covers 102 large financial institutions in the euro area, is the ECB's Supervisory Reporting data (SUP). Starting from 2014 Q4, SUP provides quarterly balance sheet and income statement data for each bank directly supervised by the ECB's Single Supervisory Mechanism (SSM). Banks are directly supervised by the SSM since 2015 instead of the national authorities in the euro area member states if they are considered "significant" financial institutions in the euro area . The status is determined by the ECB and depends on the size, the economic importance and the extent of cross-border activities of the banks, and on whether it has received direct public financial assistance, see here for details from the SSM. The data is collected for supervisory purposes so it includes detailed information on the balance sheets of banks with a focus on profitability and credit risk.

We use this data to compute the realized returns on equity and individual balance sheet positions (based on income flow data and stocks). The data also includes information on the riskiness of individual bank's assets. The riskiness is expressed in regulatory risk weights (which are used to determine the capital requirements of each bank). Due to data limitations, we only have access to this information for assets which are assessed under the so-called standardized approach (around 50% of outstanding amounts for loans). This is part of the Basel framework for banking supervision under which banks can choose whether to compute their credit risk exposure under the standardized approach or using the internal ratings-based approach if they meet certain requirements, see e.g., here for the standardized approach and here for the internal ratings-based approach. We use this information to complement the data on riskiness of loans obtained from the credit register AnaCredit.

Individual Balance Sheet Items data Information on the maturity and counterparty sectors for loans and deposits is taken from the Individual Balance Sheet Items (IBSI) dataset, which is collected by the Euroystem central banks. This is a monthly dataset that starts in July 2007 and covers around 300 banks in the euro area. It includes the stocks and flows of individual banks' balance sheet positions. In particular it contains information on the stocks of loans and deposits of euro area counterparties by maturity buckets and counterparty sector.

Data on securities held and securities issued   Detailed information on the securities owned by banks is based on the Centralized Securities Database (CSDB). The CSDB contains monthly, ISIN level data on all securities issued in the euro area and/or in euro since September 2013. It includes information on outstanding amounts, rating, and maturity at the ISIN level. In addition, the Securities Holdings Statistics Group (SHSG) dataset provides information on which of these securities are held by which bank for around 150 euro area banking groups.

Credit Register and firm data   The euro area credit register, AnaCredit, covers close to the universe of corporate loans in the euro area. AnaCredit collects harmonized data on individual loans from all euro area member states. Banks are required to report information on loans to firms for exposures above €25,000. Information is available at a monthly frequency, since in September 2018. For each loan, we observe the outstanding nominal amount, the applied interest rate, the probability of default of the borrower and the amount in arrears, among others. The data also includes a wide set of borrower attributes such as firm sector of economic activity and geolocational data. We add further information (investment, assets, profits, sales among others) on the firms in AnaCredit using Bureau Van Dijk's Orbis database on listed and unlisted firms.
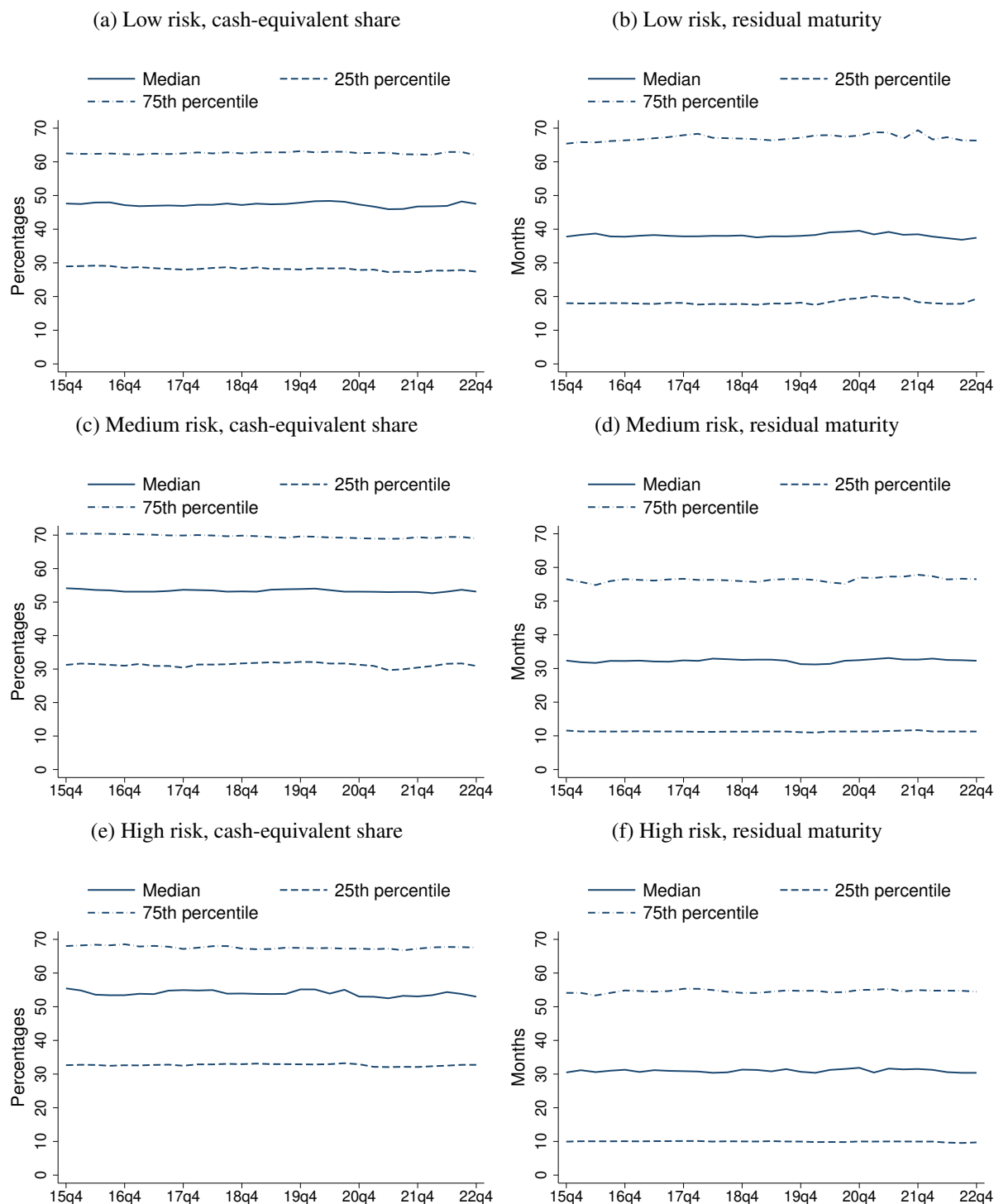
B   Additional charts and tables

Figure B.1: CES, residual maturity and distance to inception date for loans to firms, by risk (input into RP algorithm)
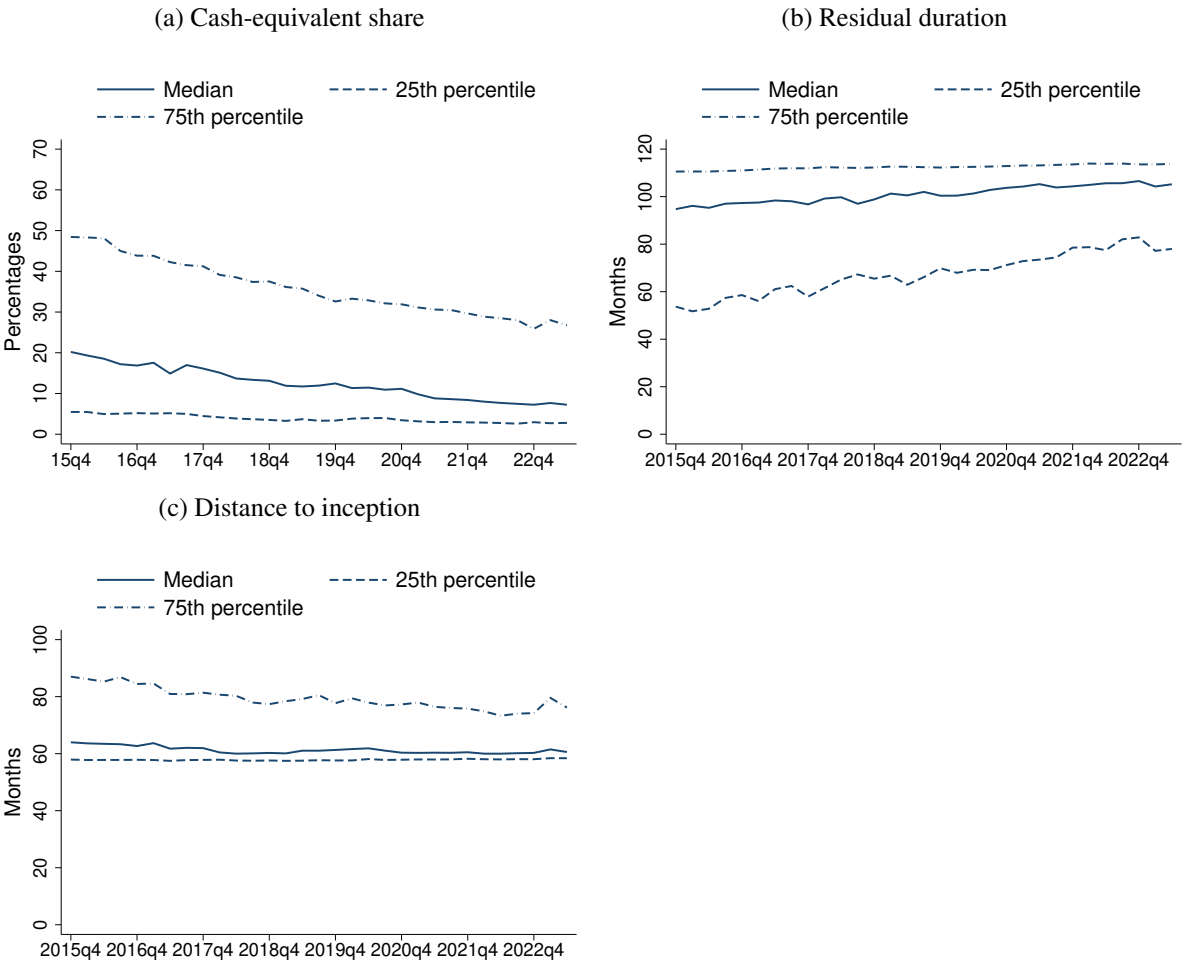
(a) Cash-equivalent share

(b) Residual maturity


(c) Distance to inception
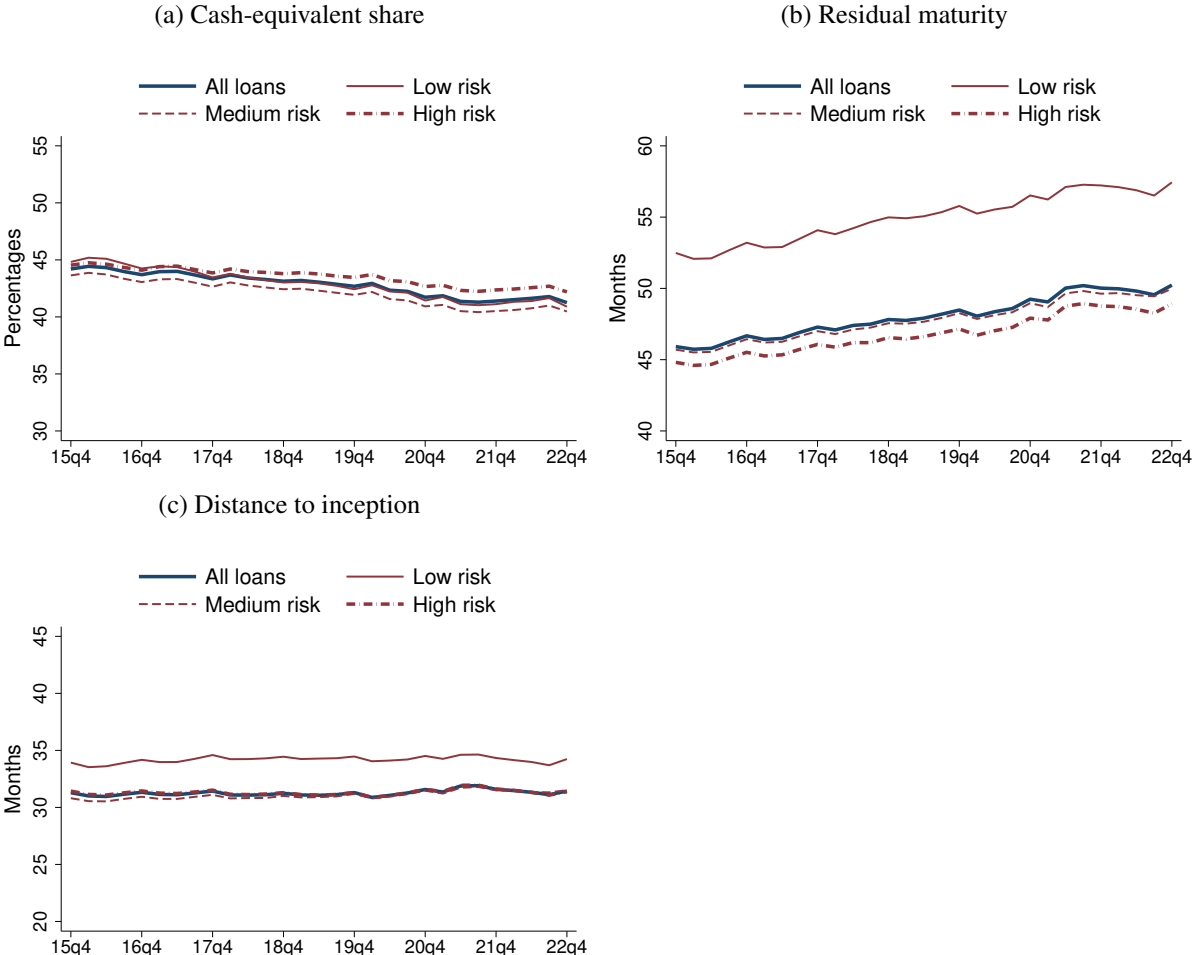
Notes: Weighted averages of bank level CES, residual duration and distance to inception which are estimated based on Ana-Credit and IBSI data, as described in Section 2.2.

Figure B.2: Distribution of CES and residual maturity (input into RP algorithm) by firm risk

(a) Low risk, cash-equivalent share

(b) Low risk, residual maturity

(c) Medium risk, cash-equivalent share

(d) Medium risk, residual maturity

(e) High risk, cash-equivalent share

(f) High risk, residual maturity

Notes: Distribution of bank level CES and residual duration to inception which are estimated based on AnaCredit and IBSI data, as described in Section 2.2.

Figure B.3: CES, residual maturity and distance to inception date for loans to households (input into RP algorithm)

(a) Cash-equivalent share

(b) Residual duration

(c) Distance to inception

Notes: Distribution of bank level CES, residual duration and distance to inception which are estimated based on IBSI data, as described in Section 2.2.

Figure B.4: Non-performing loans ratios by loan type
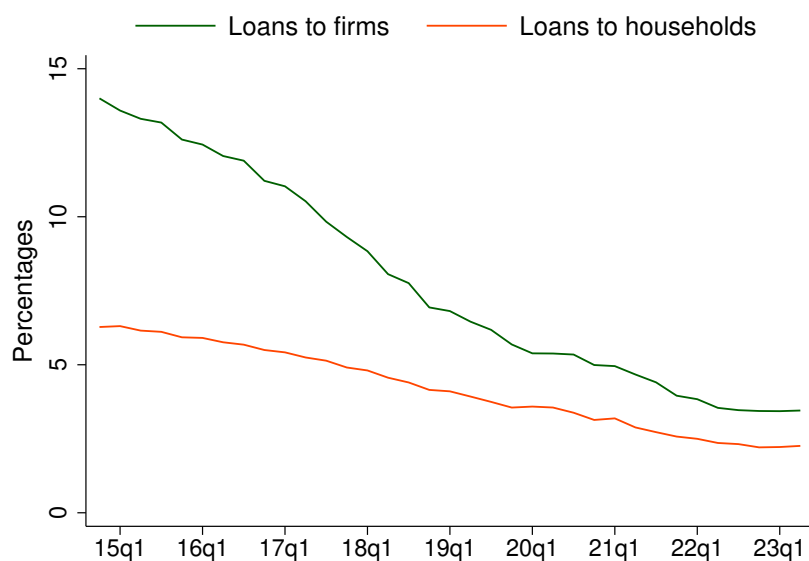
Notes: Share of non-performing outstanding amounts in total outstanding amounts. Based on a balanced panel of significant institutions (93 SIs) under the supervision of the ECB.

Figure B.5: Price-to-book ratios across euro area sectors
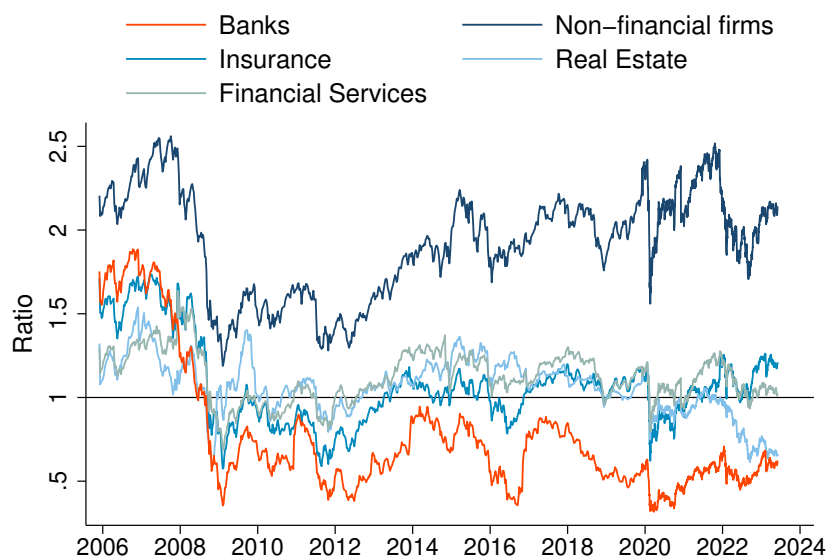
Notes: Price-to-book ratios are computed based on the market value of the bank computed as share price*number of shares and the book value measured by the most recent available information on the book value of banks' equity from financial reporting.

Figure B.6: Impact of changes in potential determinants of banks' edge orthogonal to banks' net worth
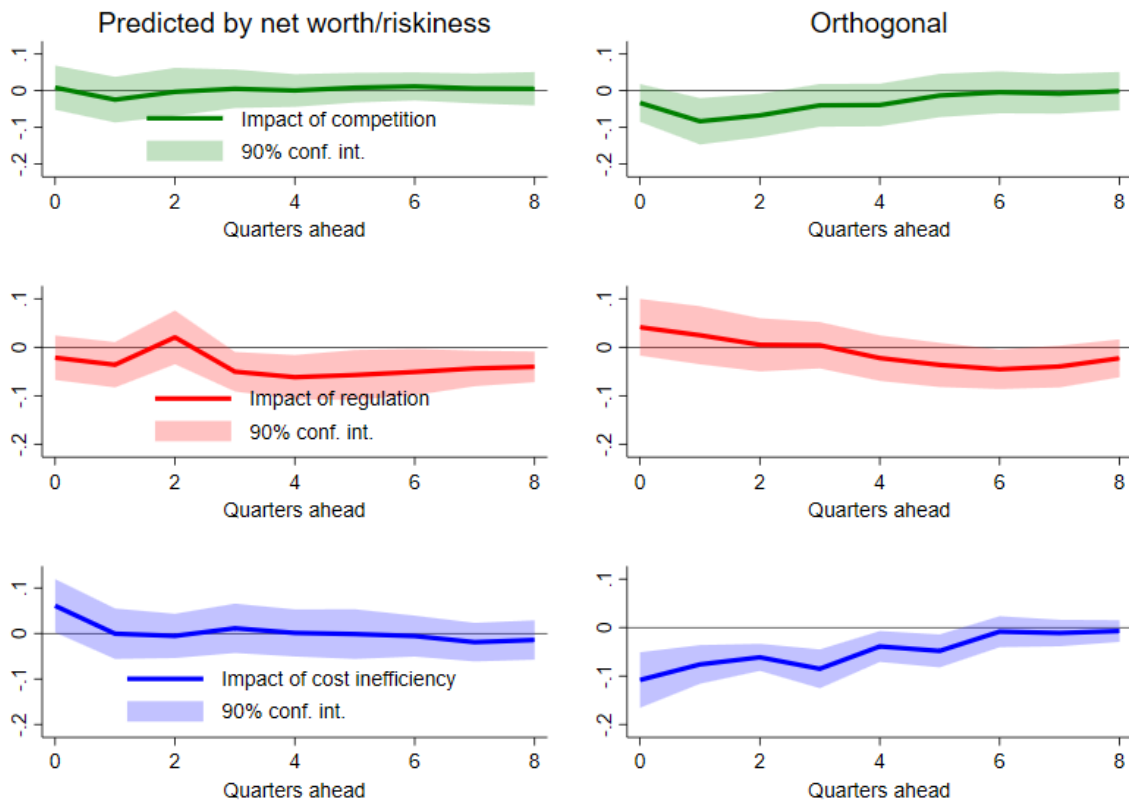

Notes: Charts show the change in total edge relative to 1 standard deviation for one a standard deviation of the change in each potential determinant. Dependent variable and regressors are standardised. Each determinant is split between the part predicted by (lagged) measures of net worth/riskiness (CET1 ratio, leverage ratio, average risk weight) and the part orthogonal to these measures. Specification with bank and country-time FE, cluster at bank level.

Figure B.7: Impact of cost inefficiency on banks' edge by balance sheet item
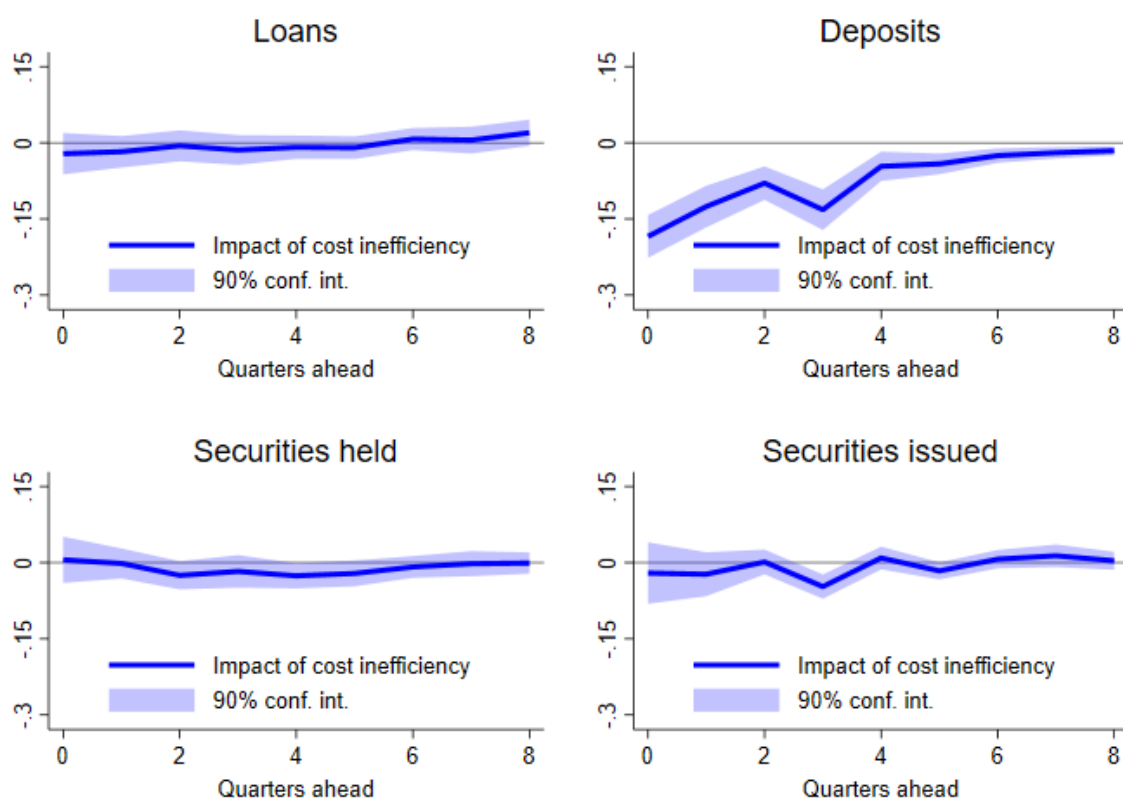
Notes: Charts show the change in total edge relative to 1 standard deviation for one a standard deviation of the change in cost inefficiency. Dependent variable and regressors are standardised. Each determinant is split between the part predicted by (lagged) measures of net worth/riskiness (CET1 ratio, leverage ratio, average risk weight) and the part orthogonal to these measures. Specification with bank and country-time FE, cluster at bank level. Edges for liabilities are multiplied by -1 so they represent the contribution of the respective item to the aggregate edge.

Figure B.8: Change in workplace mobility since December 2019 (number of months equivalent to full lockdowns)
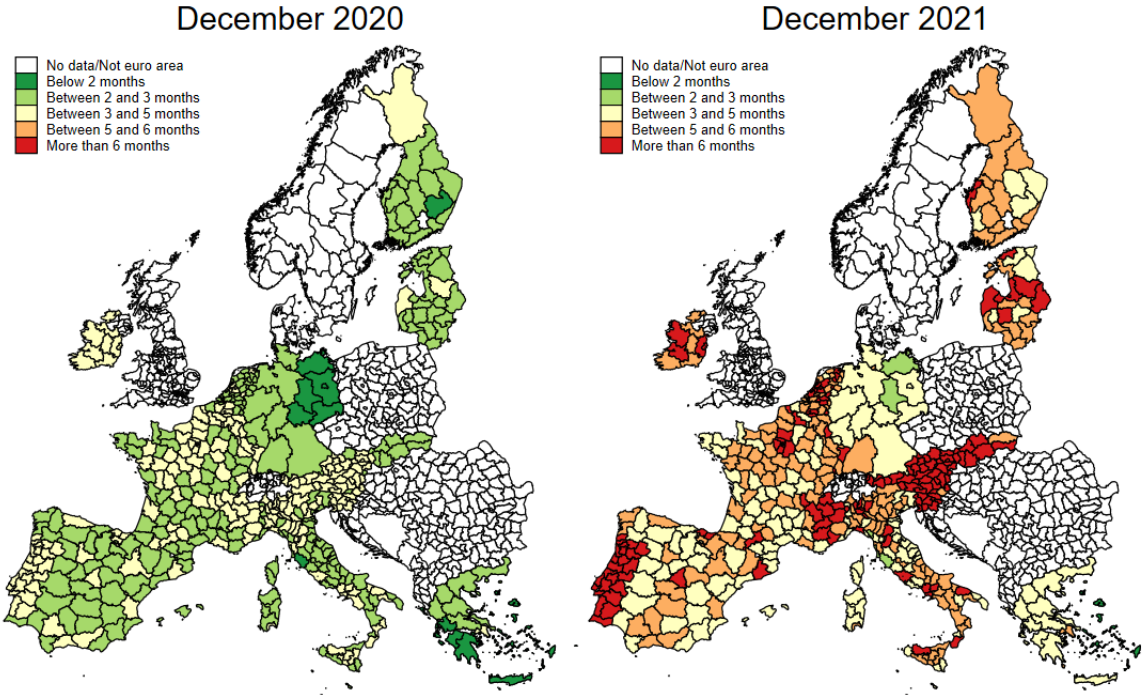
Notes: For each NUTS3 geolocational classification (or higher, as available in the raw data), we compute monthly averages of the percentage deviations from the December 2019 baseline of Google mobility in workplaces. For example, we interpret a monthly average deviation of 100% as the equivalent of a full lockdown implemented in a given location in that month, an average deviation of 50% as the equivalent of half a month of full lockdown or of a full month of partial (50% of potential mobility) lockdown. We then cumulate these deviations over months since December 2019. For example, a cumulated change in monthly averages of workplace mobility by December 2020 of 150% is the equivalent of a month and a half of full lockdowns implemented in a given location between December 2019 and December 2020. The two panels of the figure report, for each NUTS3 classification, the cumulated deviations in workplace mobility since December 2019 until December 2020 (left panel) and December 2021 (right panel).

Figure B.9: Relation between exposure to lockdowns, policy support and banks' edge – other support measures
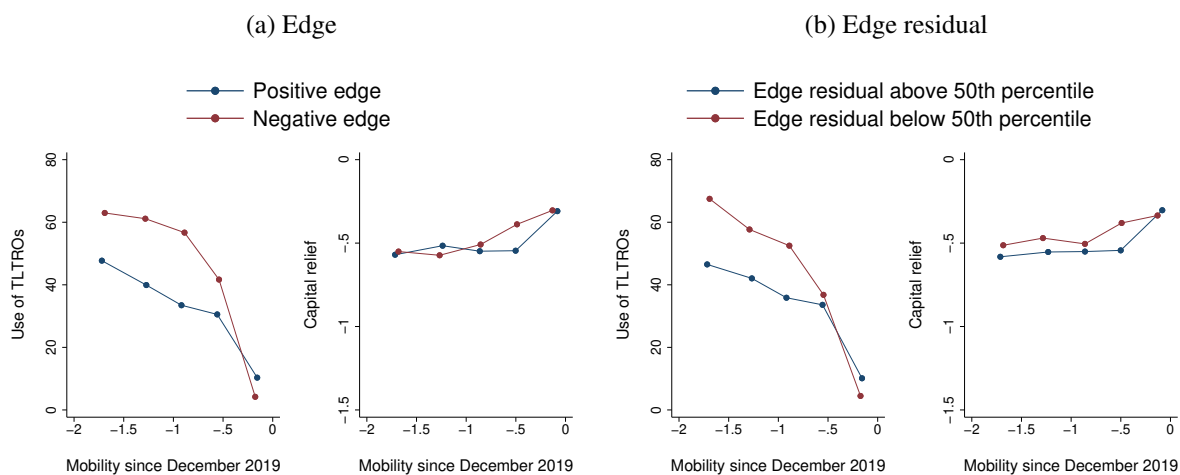
(a) Edge

(b) Edge residual

Notes: Data split into 5 bins for banks with positive edge/value above the 50th percentile (blue) or negative edge/value below the 50th percentile (red) in December 2019. Y-axis are changes with respect to level in December 2019 until June 2021. Use of TLTRO is measured as the share of TLTRO funding in eligible lending of the banks. Capital relief is measures as the percentage point decline the bank's individual capital requirement. X-axis are deviations in mobility in workplaces from baseline cumulated since December 2019 (mobility). Exposure of banks is based on weighted averages of cumulated deviations in workplace mobility across locations in which each bank is present, where weights are outstanding loans of each bank in a given location at each point in time. Residuals results from bank-level regressions of the edge on the CET1 capital ratio, the leverage ratio and the average risk weight.

Figure B.10: Euro area bank profitability and market assessment

(a) Annual return on equity

(b) Price-to-book ratios
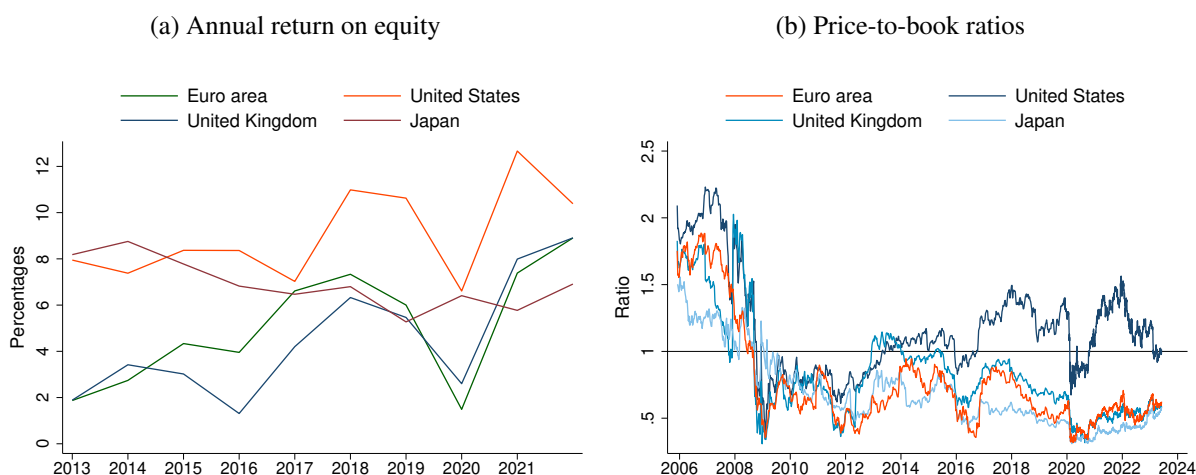
Notes: Data for annual returns weighted by banks' total equity. The annual return on equity is based on a balanced sample of 76 institutions for the euro area, 15 for the UK, 79 for Japan, and 167 for the US. Price-to-book ratios are computed based on the market value of the bank computed as share price*number of shares and the book value measured by the most recent available information on the book value of banks' equity from financial reporting.

Table B.1: **Descriptive statistics for bank sample**

Variable	Definition	Mean	Std. dev.	Min	Max	Observ.
Edge	Difference between realized return and replicating portfolio return, in %	-1.9	6.3	-35.56	23.02	2833
Change in edge	Quarterly change in edge, in pp.	0.29	1.91	-5.62	7.56	2706
Realized return, total	Ratio of net income to book equity, in %	2.71	4.35	-17.75	17.51	2833
Replicating portfolio return, total	Share of net income flow from replicating portfolio in book equity, in %	4.95	6.25	-20.06	40.77	2833
Realized return, firms	Ratio of net income on loans to firms to outstanding loans to firms, in %	2.00	1.15	-1.07	11.57	2774
Realized return, households	Ratio of net income on loans to households to outstanding loans to households, in %	1.98	1.37	-2.09	9.64	2787
Realized return, securities held	Ratio of net income on debt securities held to outstanding debt securities, in %	0.69	1.09	-3.47	6.39	2802
Realized return, securities issued	Ratio of net expenses on debt securities issued to outstanding debt issued, in %	2.05	1.34	-0.07	9.60	2687
Realized return, deposits	Ratio of net expenses on deposits to outstanding deposits, in %	0.77	0.93	-0.69	8.24	2790
Replicating portfolio return, firms	Replicating portfolio return on loans to firms (see text for details), in %	0.93	0.75	-0.48	3.09	2272
Replicating portfolio return, households	Replicating portfolio return on loans to households (see text for details), in %	1.44	0.76	-0.47	3.97	2815
Replicating portfolio return, securities held	Replicating portfolio return on securities held (see text for details), in %	0.65	0.76	-0.54	2.61	2833
Replicating portfolio return, securities issued	Replicating portfolio return on securities issued (see text for details), in %	1.00	0.86	-0.45	4.07	2833
Replicating portfolio return, deposits	Replicating portfolio return on deposits of firms and households (see text for details), in %	0.09	0.84	-0.55	3.90	2833
Cost inefficiency	Cost to income ratio, in %	46.20	18.26	-2.62	117.53	2833
Change in cost inefficiency	Quarterly change in cost to income ratio, in pp.	-0.32	14.07	-55.88	56.22	2833
Competition	Indicator on whether competition from non-banks affect loan demand by firms in last 3 months (-1: increase in loan demand, 0: no change in loan demand, 1: decrease in loan demand)	0.05	0.21	0.00	1.00	1911
Regulation	Regulatory capital requirement as share of total risk-weighted assets, in %	10.06	1.68	2.78	25.38	2605
Change in regulation	Quarterly change in regulatory capital requirement, in pp.	0.01	0.67	-3.22	3.76	2526
Avg. risk weight	Average regulatory risk-weight of bank portfolio, as share	0.39	0.14	0.05	0.99	2829
Leverage ratio	Tier 1 capital over total assets, in %	6.13	2.42	2.14	31.76	2829
CET1 ratio	Common Equity Tier 1 (CET1) capital over risk-weighted assets, in %	15.06	6.63	1.50	104.34	1709
Monetary policy surprise	First principal component of high-frequency interest rate surprises around ECB monetary policy events	0.10	3.33	-6.59	10.03	2833
Excess liquidity	Share of excess liquidity (CB reserves in excess of required reserves) in total liabilities, in %	8.72	8.07	0.00	57.49	2817
Securities holdings	Share of government bond holdings in total assets, in %	7.77	6.89	-6.77	60.19	2819
Deposit ratio	Share of total deposits in total liabilities, in %	39.57	23.56	0.00	91.19	2831
Reliance on TLTROs	Share of outstanding TLTRO liquidity in total liabilities, in %	4.76	5.26	0.00	23.59	2831

Notes: Descriptives for sample of 112 banks between 2015Q4 and 2023Q2 for which we can compute the edge.

Table B.2: **Descriptive statistics for firm-bank sample**

Variable	Definition	Mean	Std. dev.	Min	Max	Observ.
Edge in %	Difference between realized return and replicating portfolio return, in %	-1.72	5.33	-26.49	23.02	16,698,211
Loan volume	Log of loan volume	-1.88	1.90	-18.42	9.11	16,698,211
Residual of cost inefficiency	Cost to income ratio, in %	5.90	14.66	-50.80	83.42	16,698,211
Residual of competition	Indicator on whether competition from non-banks affect loan demand by firms in last 3 months (-1: increase in loan demand, 0: no change in loan demand, 1: decrease in loan demand)	0.07	1.44	-0.89	7.45	16,698,211
Residual of regulation[1]	Regulatory capital requirement as share of total risk-weighted assets, in %	-0.82	0.98	-3.50	4.80	16,698,211
Avg. risk weight	Average regulatory risk-weight of bank portfolio, as share	0.39	0.08	0.05	0.99	16,698,211
Leverage ratio	Tier 1 capital over total assets, in %	5.68	1.11	2.14	31.76	16,698,211
CET1 ratio	Common Equity Tier 1 (CET1) capital over risk-weighted assets, in %	13.48	2.38	8.46	107.14	16,698,211
Excess liquidity	Share of excess liquidity (CB reserves in excess of required reserves) in total liabilities, in %	9.65	6.44	0.00	50.19	16,698,211
Securities holdings	Share of government bond holdings in total assets, in %	9.10	4.95	0.00	33.32	16,698,211
Deposit ratio	Share of total deposits in total liabilities, in %	46.30	11.78	0.00	87.40	16,698,211
TLTRO reliance	Share of outstanding TLTRO liquidity in total liabilities, in %	10.23	4.94	0.00	23.45	16,698,211

Notes: Descriptives for sample as used in Table 1, observations are bank-firm-month. The sample consists of 1,706,844 bank-firm relations between 608,388 firms and 104 banks, distributed across all 19 euro area countries (members as of 2022), followed between 2018Q4 and 2023Q2 (19 quarters).
[1] For details on how the residuals are constructed, see the main text.

Table B.3: **Descriptive statistics for firm sample during pandemic**

Variable	Definition	Mean	Std. dev.	Min	Max	Observ.
Change in investment rate	Change in share of firm's long-term investments over total assets, in p.p.	6.91	29.66	-44.89	87.69	181,934
Loan volume (predicted)	Predicted value for the log of firm's loan volume (see text for details)	-0.30	0.10	-0.64	-0.06	181,934
Log loan volume	Log of firm's loan volume	-1.74	1.50	-13.88	8.40	181,934
Firm assets	Log of firm's total assets	14.63	1.40	10.86	18.25	181,934
Firm ROA	Firm's return on assets, in %	2.40	6.91	-42.20	32.15	181,934
Firm sales per worker (in thsd)	Firm's sales per worker in Euro thousand	253	320	11	1817	181,934
Avg. risk weight	Average regulatory risk-weight of bank portfolio, as share	0.44	0.06	0.28	0.68	181,934
Leverage ratio	Tier 1 capital over total assets, in %	6.04	0.83	3.94	9.99	181,934
CET1 ratio	Common Equity Tier 1 (CET1) capital over risk-weighted assets, in %	12.79	1.10	10.39	16.74	181,934
Excess liquidity	Share of excess liquidity (CB reserves in excess of required reserves) in total liabilities, in %	3.51	1.98	0.10	16.31	181,934
Securities holdings	Share of government bond holdings in total assets, in %	9.89	3.17	0.00	20.95	181,934
Deposit ratio	Share of total deposits in total liabilities, in %	45.53	7.50	5.41	70.97	181,934
TLTRO reliance	Share of outstanding TLTRO liquidity in total liabilities, in %	8.19	2.86	0.00	14.83	181,934

Notes: Descriptives for sample as used in Table 3, observations are firms. The sample consists of 181,934 firms linked to 80 banks across 12 euro area countries (Austria, Belgium, Germany, Spain, Finland, France, Greece, Italy, The Netherlands, Portugal, Slovenia, and Slovakia).

Table B.4: **Impact of edge on banks' lending conditions – including for ROE**

	(1)	(2)	(3)
Dependent variable:	Loan volume	Loan volume	Loan volume
Edge	0.041*	0.023**	0.027**
	(0.023)	(0.011)	(0.011)
Endogenous component $\hat{\varepsilon}_{b,t}$	-0.036*	-0.022**	-0.024**
	(0.021)	(0.010)	(0.010)
ROE	-0.004	-0.001	-0.003
	(0.005)	(0.004)	(0.004)
Firm-time FE	YES	YES	YES
Bank controls	NO	YES	YES
Bank net worth measures	NO	NO	YES
Other edge determinants	NO	NO	YES
Model	CFA	CFA	CFA
Observations	16,698,211	16,698,211	16,698,211
R^2	0.43	0.43	0.43

Notes: Standard errors clustered at the bank level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.5: **Impact of edge on firms' variables**

Panel a

Dependent variable	(1) Growth of tangible investment	(2) Growth of intangible investment	(3) Growth of total assets	(4) Growth of loans	(5) Growth of employment	(6) Growth of sales
Banks' loan volume	4.486*	-8.739***	3.748**	21.448***	2.440*	-0.745
	(2.257)	(2.831)	(1.498)	(5.796)	(1.268)	(1.837)
Fixed effects	ILS	ILS	ILS	ILS	ILS	ILS
Observations	105,660	105,660	105,660	105,660	80,302	105,660
R-squared	0.05	0.02	0.07	0.03	0.07	0.18

Panel b

Dependent variable	(7) Change in ROA	(8) Change in interest rate on debt	(9) Change in EBITDA/Interest paid	(10) Change in leverage	(11) Zombie in 2020
Banks' loan volume	-0.113	0.185**	-0.484	-0.714	0.835
	(0.369)	(0.092)	(1.956)	(0.782)	(1.041)
Fixed effects	ILS	ILS	ILS	ILS	ILS
Observations	105,660	105,660	105,660	105,660	105,660
R-squared	0.18	0.05	0.05	0.14	0.07

Notes: Standard errors clustered at the main bank level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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