Real domestic effects of bank cross-border lending

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Abstract. In this paper we investigate empirically whether having a domestic banking sector that

lends more abroad is beneficial for the productivity of the domestic real economy. We investigate

this question by using both cross-country, cross-country / cross-sector and within-country / cross-

firm panel data, thus providing aggregate and micro evidence. The analysis, that comprises the

estimation of several OLS, system GMM, local projection and IV models, points to the beneficial

role of a higher internationalization of the domestic banking system on the productivity of the

domestic economy. Results emerge both when using cross-country data from a panel of

advanced economies and cross-country / cross-sector data from a panel of European economies,

and are confirmed when adopting a more granular approach by using UK firm and bank panel

data. This effect is stronger when the domestic banking system lends more to firms in foreign

advanced economies, does not come only from exporting firms, and is more pronounced during

the early phase of a new banking relationship. In contrast, the inflow of lending from foreign banks

does not result in productivity improvements for the domestic real economy.

Keywords: banks, international lending, productivity, TFP, financial openness

JEL codes: G10, G15, G18, G21, O4

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1. Introduction

A global financial centre has a dual role: a domestic financial centre, that channels finance into what is typically an advanced economy, and a host venue for international financial activity. It is important to consider whether the latter role can exert either positive or negative spillover effects on the former, not only during a crisis, but also in normal times. Besides being a host for foreign financial intermediaries, domestic ones are also typically internationally active. Cross-border lending by domestic banks can improve geographical risk diversification, which in turn can improve the resilience of their domestic lending during a banking crisis (Doerr and Schaz 2021). However, cross-border interbank lending by domestic banks can expose them to shocks from banking crisis abroad, which in turn can tighten credit conditions domestically (Hale et al. 2020). Another benefit from cross-border lending by domestic banks, not linked to the impacts of economic and / or financial crises, is that it can help domestic non-financial corporations (NFCs) customers to export into (eg, Paravisini et al. 2023) / import from (Alfaro et al. 2025) countries where they are lending.

Hypothesis generation. This paper investigates whether cross-border lending by domestic banks generates positive spillovers by enhancing the productivity of the domestic economy. Arguably, there can be two opposing effects. On the one hand, cross-border lending might crowdout domestic one. Domestic banks engaged in international lending have the option to channel savings raised domestically to pursue higher returns by lending / investing abroad (eg, Obstfeld 1994; and Agénor 2003). This in turn might entail negative productivity consequences for the domestic real economy to the extent that financial constraints faced by NFCs worsen as a result.

On the other hand, the knowledge gathered through cross-border lending could improve the ability of domestic banks to screen and monitor domestic NFC borrowers, particularly among those facing financial constraints but with the potential for growth through productivity improvements. To the extent that foreign lenders tend to focus on established NFCs (eg, Agénor 2003),² which are typically less likely to face financial constraints and tend to be closer to the

¹ The same applies to the case of foreign branches and subsidiaries raising funds but not lending in the host-country.

² First, foreign lenders may face greater adverse selection with respect to the pool of domestic NFC borrowers compared to domestic lenders, thus focusing on established NFCs which are typically less opaque. Second, lending to foreign large, established NFCs is more likely to give rise to scale and scope

productivity frontier, the posited positive spillover effects in terms of productivity improvements by domestic NFC borrowers should only arise from cross-border lending by domestic banks, rather than foreign banks lending to domestic NFC borrowers. Indeed, the same focus on established NFCs when lending abroad would allow domestic banks to gather intelligence relevant to their lending to less-established domestic NFCs, where there is more room for productivity improvement.

In addition, the lender can pass on knowledge gathered by lending abroad that domestic NFCs borrowers can benefit from. Whilst the extant literature has so far highlighted this information-sharing channel mainly with respect to exporting / importing domestic NFCs borrowers benefiting from knowledge about foreign markets (eg, Paravisini et al. 2023; and Alfaro et al. 2025), this channel could be of more general validity, for example, by conveying information on best business practices and trends.

In conclusion, we posit that cross-border lending by domestic banks can have a positive spillover effect in terms of rate of growth of productivity by domestic NFC borrowers, but the same does not apply to foreign banks lending to domestic NFC borrowers.

Methodological approach. This paper aims at providing evidence on whether cross-border lending by domestic banks affects the productivity of the domestic real economy, by combining both cross-country, cross-country / cross-sector and within-country / cross-firm panel data.

First, we employ cross-country panel data from the Bank of International Settlements (BIS) to build a country-level measure of cross-border lending of the domestic banking sector and exploit cross-country and temporal variation to gather empirical evidence. BIS statistics provide granular data on the geographic composition of the cross-border lending portfolio of domestic banks for a large panel of countries. We then use country-level data on productivity as our main dependent variable in a traditional OLS FE equation. Since endogeneity can affect the relationship between cross-border lending in the banking sector and the productivity of the real economy, we resort to GMM estimation and to local projection to mitigate such concerns. In this framework, we test whether a higher degree of openness to international markets of the domestic banking sector translates into higher productivity at home.

Second, we merge the country-level measure of cross-border lending described above with cross-country / cross-sector panel data on productivity for a subset of European countries

economies with respect to the rest of the global commercial banking activities undertaken by internationally active banks.

from CompNet to investigate whether our results are confirmed when adopting a more granular view.

Third, using confidential administrative data we calculate a bank-level measure of crossborder lending for UK banks. We then combine this information with balance sheet data from UK NFCs, from the FAME dataset by BvD. The latter enables us to calculate productivity at firm level. The dataset also provides information on the banks with whom each non-financial company has a secured lending relationship. We then proceed to test whether UK NFCs exhibit higher productivity growth after establishing a lending relationship with banks with more lending to foreign NFCs, especially when they are located in major advanced economies. In this setting we can saturate regressions with different levels of fixed effects. In particular, we use bank, firm and industry*location*year fixed effects, a specification that has been shown to capture demand effects that would bias our results if not taken into account (Degryse et al. 2019). To further reduce concerns on endogeneity we also resort to a Bartik instrument, as in Kneer and Raabe (2024), and we restrict our sample to a macro-sector that performed particularly poorly in the UK with respect to other advanced economies in the years before the beginning of our data. Finally, we test whether our results merely depend on a better support provided by internationalised banks to exporting firms, or if they arise also for purely domestic NFCs; and if the intensity of the effects varies in the different stages of bank-firm relationship.

Summary of the results. Our results point to the beneficial role of international lending by the domestic banking sector on the productivity growth of the domestic real economy. Cross-country results indicate that a 1% increase in foreign lending by domestic banks is associated with an increase in the annual growth rate of productivity of the domestic economy in the range of 0.18-0.74 percentage points. This effect consolidates over time. Similar findings emerge when moving to the cross-country / cross-sector panel dataset and are confirmed when adopting a within-country / cross-firm panel approach using UK data. In particular, we find that results come especially from banks' lending to firms located in foreign G7 economies, in line with our information-based positive spillover channels. Moreover, results emerge both from exporting and non-exporting firms and show up in a slightly more intense fashion in the first years of the bank-firm lending relationship.

In contrast, we find no evidence that lending by foreign banks to domestic NFCs is associated with productivity improvements in the domestic real economy. Specifically, under the cross-country approach our findings do not point to a significant role of the inflows of loans from foreign countries on the productivity of the real economy. Similarly, under the within-country /

cross-firm approach based on UK panel data our results show that, if anything, such firms experience a decline in productivity.

It could be argued that our results from the within-country / cross-firm panel approach merely capture the fact that whilst internationalised banks may be better at screening domestic NFCs that are on the cusp of a productivity improvement, these borrowers would have been able to secure a loan even from a purely domestic lender. If so, whilst the posited information spillover effect would tend to improve the profitability of internationalised banks (ie, by reducing expected losses on corporate loans), it would not give rise to any real effects, as the ensuing productivity improvement by affiliated NFC borrowers would have been realised in any case. However, if that were to be the case, there should be no association between the level of cross-border lending by domestic banks and the productivity of the domestic economy at an aggregate level.³ Whereas, our results from the cross-country and cross-country / cross-sector panel approaches show that there is such an association, thus supporting the proposition that cross-border lending by domestic banks gives rise to positive spillover effects for the domestic real economy.

Contribution to the literature. This paper is related to two strands of literature. First, our paper adds to the vast literature on how financial development, in particular with respect to corporate bank credit in developed countries, facilitates economic growth.⁴ On the one hand, early evidence based on a cross-country / cross-sectional approach showed that growth in bank credit is positively and significantly correlated with rates of economic growth, capital accumulation and productivity growth (eg, King and Levine 1993; Levine and Zevros 1998). These results were confirmed with cross-country / panel approaches (eg, Levine et al. 2000; Beck et al. 2000; Botev, Égert, and Jawadi 2019). Of particular interest, Rioja and Valev (2004) showed that the way financial development boost growth in developed countries is by increasing productivity growth rather than accelerating capital accumulation. Rajan and Zingales (1998) used a cross-country / cross-sector, Diff-in-Diff approach to show that these positive effects are stronger in industries that rely more on external sources of finance. Using the same approach, Beck et al. (2008) found that this is especially the case for industries that due to technological reasons are naturally

³ Of course, even in this very restrictive case, in theory there should be dynamic efficiency effects whereby the improved profitability of internationalised banks means that over time they ought to gain market share at the expense of purely domestic banks, thus driving a corresponding (dynamic) efficiency improvement in the real economy, as less productive NFC borrowers find it more difficult to secure lending.

⁴ See literature reviews in Levine (2021) and Popov (2017).

composed of small firms, and Strieborny and Kukenova (2016) found that that this is especially in industries where suppliers rely on a banking relationship as a signal of trustworthiness when deciding on relationship-specific investment with buyers. Finally, studies based on cross-firm, micro evidence confirmed that financial development supports the growth of otherwise financially constrained firms (eg, Demirguc-Kunt and Maksimovic 1998; Love 2003; Brown, Martinsson, and Petersen 2012; and Berger and Sedunov 2017). We contribute to this strand of literature by using cross-country, cross-country and cross-industry and within-country / cross-firm approaches to investigate the impact of cross-border bank lending on economic growth.

Second, and more specifically, our paper relates to the literature on how cross-border lending can be beneficial to domestic NFC borrowers.⁶ This is particularly the case with respect to exporting firms borrowing from domestic banks with exposure / presence in importing countries (eg, De Bonis et al. 2015; Bronzini and D'Ignazio 2017; Caballero et al. 2018; Paravisini et al. 2023; and Berthou et al. 2024). Alfaro et al. (2025) show how US manufacturers and wholesale traders importing goods from China were better able to find an alternative supplier in a neighbouring country in response to the imposition of tariffs on Chinese imports in 2018 if they had a relationship with a bank already providing trade credit to exporters in those countries. Claessens and Van Horen (2021) showed that exports tend to be larger when a foreign bank from the importing country is present, and that entry of a foreign bank also boosts export growth to the home country of the foreign bank relative to other countries.⁷ Our contribution to this strand of

⁵ On the other hand, there is some cross-country evidence, especially focussing on the aftermath of the Great Financial Crises (GFC), showing that the relationship between financial development and growth can be non-monotonic, whereby excessive private credit growth, especially with respect to household credit, can negatively impact growth (eg, Manganelli and Popov, 2013; Ductor and Grechnya, 2015; Arcand et al., 2015; Beck et al., 2014).

⁶ See Claessens (2017) for a literature review.

⁷ More in general, it has been shown that the increase in competition as a result of the entry of foreign banks can benefit domestic NFC borrowers as a result of the improved access to financial services (eg, Claessens et al. 2001; Martinez Peria and Mody 2004; Bruno and Hauswald 2013). On the other hand, NFCs dependent on credit and with a relationship with foreign banks suffered more in their financing and real performance in the aftermath of the GFC Crisis (eg, Cetorelli and Goldberg 2011; De Haas and Van Lelyveld 2014; Ongena et al. 2015). More recently, Imbierowicz et al. (2025) found that German bank subsidiaries reduced lending to UK NFC borrowers in the aftermath of the Brexit referendum, with less profitable firms facing a larger credit crunch and financially constrained firms experiencing negative real outcomes.

literature is to show that the beneficial effects from cross-border lending by domestic commercial banks is not limited to exporting / importing NFC borrowers.

Doerr and Schaz (2021) showed that banks with a more geographically diversified portfolio of syndicated loans maintain higher loan supply during banking crises in borrower countries. The authors document that their higher loan supply has significant effects on firm performance, both in terms of investment and employment growth. Such effects are stronger for domestic banks with an internationally diversified portfolio, whereas are weaker for foreign banks with a concentrated exposure. The authors argues that this effect is because diversified banks can better raise funding than non-diversified ones. We do not limit our investigation to periods of banking crisis and, in our within-country / cross-firm approach rely on bank – NFC borrower pairing where the bank is in direct contact with the borrower, whereas as the authors point out syndicated loans participants are usually not in direct contact with the borrower, but merely supply credit. Therefore, the positive effects identified in Doerr and Schaz (2021) could not be attributed to other channels such as improved screening / monitoring and information sharing.

Finally, Liu and Pogach (2017) show that cross-border lending by US global banks does not crowd-out lending to domestic NFCs, but for during the GFC when raising capital to expand lending was prohibitively expensive. We add to these findings by exploring whether there are potential positive spillovers from cross-border lending that benefit domestic NFCs.

The paper proceeds as follows. In Section 2 we describe the various datasets we use. In Section 3.1 we present results under the cross-country approach, in Section 3.2 we present results under the cross-country / cross-sector approach, and in Section 3.3 we present the results under the within-country / firm level approach. Section 4 concludes.

2. Data description

In this paper we adopt three approaches using: *i)* cross-country data on the internationalisation of the banking sector from the BIS, plus cross-country data on growth and productivity from the OECD; *ii)* cross-country and cross-industry data for a subset of European countries from the CompNet dataset; and *iii)* UK cross firm data from the FAME dataset by BvD matched with administrative and confidential UK cross-bank data on cross-border lending collected by the Prudential Regulation Authority.

2.1 Cross-country approach

Under the cross-country approach, we first construct a measure of internationalization of a country's domestic banking sector based on the BIS Consolidated Banking Statistics (BIS, 2024)

dataset description of foreign claims.8 Cross-border claims refer to loans or other claims extended to non-residents by offices of the bank (eq. a claim booked at headquarters on a borrower abroad) while local claims of foreign affiliates refer to claims by the bank's overseas branches and subsidiaries on borrowers in the host country. For example, if a UK-based bank lends directly from its London office to a firm in Italy, that loan is a cross-border claim on Italy. If instead the bank's Italian subsidiary or branch extends a loan to an Italian firm, it is recorded as a local claim in Italy by a foreign (UK) affiliate. Together, these two components comprise the UK bank's total foreign claims on Italy. We focus on domestically headquartered banks as the lending institutions in our dataset.9 We utilize the longest available time series from the BIS CBS, which spans for some of our reporting countries the early 1980s through to 2024, on a quarterly basis. In the initial years, the data were collected at a lower frequency - the CBS were originally published semiannually (end-June and end-December). A major enhancement in the BIS statistics occurred when quarterly reporting was introduced for the CBS on the immediate-counterparty basis commenced in 2000 Q1, replacing the prior semi-annual schedule. In our analysis, we incorporate the semi-annual observations prior to 2000 and the quarterly observations thereafter. For consistency, we treat the semi-annual data points as if they were quarterly period-end positions (since mid-year and year-end roughly correspond to Q2 and Q4). All foreign claims are measured in US dollars as reported by the BIS, and we do not apply additional exchange-rate adjustment or normalization. The immediate-counterparty data are not exchange-rate adjusted by BIS; large

⁸ Foreign claims are defined as the sum of cross-border claims and the local claims of foreign affiliates. In other words, any claim on a borrower outside the bank's home country is counted as a foreign claim. Conversely, claims on borrowers resident in the bank's home country are domestic claims.

⁹ According to BIS data dictionary, this corresponds to bank type 4B, which represents banks controlled by parent entities in the home reporting country (i.e. the consolidated banking groups of that country). The 4B series captures the full worldwide claims of each country's banks, including both their domestic and foreign positions. In essence, using 4B ensures we capture the entire foreign portfolio of each country's banking system. As a robustness check, we also consider the 4R series, which represents "domestic banks, excluding domestic positions. The 4R data remove home-country claims from 4B, isolating just the international component (claims on non-residents). In practice, our methodology of taking 4B and subtracting domestic claims (by excluding home-country counterparties) is equivalent to using the 4R series. We verified that the foreign claims totals derived from 4B (omitting home claims) closely match the 4R figures, confirming that our results are not sensitive to whether we use the direct 4R data or construct foreign claims from the 4B data. We therefore report results based on 4B for completeness, consistent with BIS publications, and note that they are robust to the 4R definition.

currency fluctuations could affect nominal claim values, but we follow standard practice in using the raw positions. ¹⁰ We include all BIS reporting countries that provide the relevant consolidated banking data. This comprises the major advanced economies and financial centres, as well as some emerging economies that joined the reporting panel in the 2000s. In total, about 30 national banking systems are represented accounting for an estimated above 95% of global cross-border banking claims by the 2000s. See BIS (2019) for further details on the data and methodology.

We visualize our constructed foreign claims variable by plotting the percentage of global foreign claims by country/economic area from 1983-2023 in Figure 1. Each stack in the chart represents the distribution of all BIS-reporting banks' foreign claims at a given quarter, broken down by the nationality of the banks.

[Figure 1]

Overall, Figure 1 highlights how the landscape of financial globalization of the banking sector as measured by our foreign claims measure, has shifted: whereas the late 20th century was first dominated by Japanese banks and then by European (especially Eurozone) banks, the post-2008 era features a more balanced distribution in which no single region utterly dominates global foreign lending. The consistent presence of the UK banking sector as a proportion of all total foreign claims reflects its role as a global financial sector and motivates us in the paper to examine in a more granular fashion the relationship between UK banking sector globalization and UK-firm level productivity.

We combine BIS data with variables coming from other sources. We use three main dependent variables from the OECD Productivity Statistics (OECD, 2024). First, we use a classical and straightforward proxy for labour productivity, the growth rate of GDP per hour worked. Since we want to focus on the impact of bank international lending on the productivity of the domestic real economy, we additionally use the growth rate of GDP per hour worked in manufacturing as dependent. We do this to avoid that our results merely reflect the impact of greater financial openness on the productivity of financial firms, and not on the real economy. Finally, we also use the growth rate of Multifactor Productivity. As explained by the OECD, it "reflects the overall efficiency with which labour and capital inputs are used together in the production process. Changes in MFP reflect the effects of changes in

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¹⁰ BIS reporting guidelines note that immediate-borrower claims are reported in USD at each period's exchange rates, and caution that trend analysis may need to account for exchange rate movements. In our construction, we focus on shares and log-differences which partially mitigate currency effects, and we also follow others (e.g. Houston et al. 2012) in winsorizing extreme changes to address outliers.

management practices, brand names, organizational change, general knowledge, network effects, spillovers from production factors, adjustment costs, economies of scale, the effects of imperfect competition and measurement errors. Growth in MFP is measured as a residual, i.e. that part of GDP growth that cannot be explained by changes in labour and capital inputs". All dependent variables are winsorized at the 1st and 99th percentile.

Figure 2 plots the evolution of the average annual productivity growth in our sample for our three key measures. GDP per hour worked (blue line), GDP per hour worked in manufacturing (red-dashed line) and Multifactor Productivity (purple striped line). Despite differing levels of volatility, all three series exhibit broadly similar tends overt time. Each measure shows a noticeable decline as expected during the global financial crisis (2009-2010), followed by a partial recovery and a return to pre-crisis trajectories, although these average hides considerable heterogeneity in post-GFC experiences across economies. As can be clearly seen GDP per hour worked in manufacturing is the most volatile variable, with a sharp contraction, near 5%, during the crisis and a subsequent short-lived rebound exceeding 7% growth. In contrast multifactor productivity and GDP per hour worked display smoother dynamics. On average GDP per hour worked hovers around a 2.5% growth rate, consistent with long run productivity trends across advanced economies although the three variables show a negative trend from the beginning to the end of our sample.

[Figure 2]

We also use a number of country-level variables as controls in our regressions. We retrieve the *Regulatory Quality index*, *R&D expenses to GDP*, the *Human Capital Index*, *Exports to GDP* from the World Bank World Development Indicators database (2024). We also include the *Economic Complexity by Hidalgo and Hausmann (2009)*.

Since productivity data are at annual level, for each year we keep foreign claims as of Q4. In our regressions, we use the variable *InternationalLending (log)* as main regressor, the natural log of foreign claims as defined above.

Data on productivity variables or controls are missing for a number of years and countries. All in all, our cross-country sample consists of annual data from 21 countries from 1998 to 2019. Table A.1 in the Appendix reports the countries in the final sample, while in Table A.2 we present descriptive statistics for the country-level dataset.

2.2 Cross-country / cross-sector approach

In the second part of the paper we use cross-country / cross-sector data from the 9th vintage of CompNet (CompNet 2022). It provides micro-aggregated firm-level-based information at the

industry-country level from 22 European countries, with data mostly coming from harmonized data collection protocols by national statistical institutes. CompNet provides different datasets, with data aggregated over macro-sector, country, and 2- digit industry-code based on NACE rev. 2. Each vintage is available for two samples: first using the entire sample of firms available in each country and second including only firms with 20 or more employees, given that in some countries firms are mandated to report their balance sheet data only when reaching a certain size. Moreover, for each dataset, CompNet provides both an unweighted and a weighted version, where the latter tis based on a reweighting procedure to generate the micro-data-based aggregate statistics for the target population in order to limit sampling differences within and across countries. To maximize the number of countries in the sample, we resort to the weighted sample including only firms with 20 or more employees (20e). Also, for the same reason we rely on the macro-sector aggregation (single-digit industry classification based on the NACE Rev. 2 sections) rather than the more granular (2-digits) one that would, in particular, exclude the UK. The 20e dataset includes data from 1997 to 2021 from 9 macro-sectors over 22 countries. A very broad set of variables is available and for each of them, the dataset lists its weighted average, median, different percentiles and other statistics. However, the time and sector coverage differ significantly between countries. To perform our empirical analysis, we retrieve from CompNet the following variables: (weighted) average growth rate of real revenues per employees, real investment, a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. All the variables are country-sector weighted averages.

2.3 Within-country / cross-firm approach

Finally, regarding the within-country / cross-firm approach, we use confidential regulatory data on UK banks combined with balance sheet data from UK non-financial companies, coming from the FAME dataset by BvD. Banks report detailed information on the geographic breakdown of their lending activity, according to the residency of each loan's counterparty. We use such information to build a measure of bank-level internationalization from a lending perspective. In particular, we calculate the variable *Foreign\Tot.Lending* that is the bank-level percentage of loans to NFCs that goes to foreign NFCs.¹¹ Additionally, since our main hypotheses rely on knowledge transfer on best practices and other soft information from the bank to the client firm, we restrict our focus

¹¹ Regulatory data used in this paper come from Covi and Gu (2022). In particular, the internationalisation data at bank level is derived from COREP F.20. To calculate this percentage, we treat loans to Guernsey, Isle of Man and Jersey as domestic loans.

on lending to major advanced economies. Those are the countries from which most likely the domestic bank is able to gather useful information to import at home, since they are the most productive ones and at the frontier of technology in most sectors. Hence, we calculate the Variable $G7\Tot.Lending$, that is the ratio of loans to NFCs located in G7 countries excluding the UK over total NFCs loans.

Banks started reporting information on the geographic breakdown of their lending activity since 2014. However, the number of reporting banks between 2016 and the end of 2017 is rather low. Overall, we prefer starting our analysis from 2018, when the number of banks providing detailed information stabilizes. This also avoids considering the structural break caused by Brexit that could bias our results. Overall, our bank-level measure of internationalization is available from 2018 to 2024. Data are quarterly, but since we will match these with firm-level annual balance sheets, we only keep the last quarter of the year. ¹² We use the regulatory classification of domestic and foreign banks and divide our sample in domestic banks and foreign ones.

Figure A.1 in the Appendix reports the evolution of the average of $Foreign\Tot.Lending$ and $G7\Tot.Lending$ considering the universe of UK (domestic) reporting banks. After a constant decline in the two variables in the initial years of the sample, both dimensions are experiencing a slightly increasing trend from 2022. On 2024 the average value of $Foreign\Tot.Lending$ is around 20%, while the value halves for $G7\Tot.Lending$. The averages hide significant heterogeneities in the distribution of the internationalisation patterns (see Figure A.2), with more than 25% of banks not reporting any loans to foreign NFCs, and the top 5% of domestic banks specialized in foreign markets reporting a value of almost 90% for $Foreign\Tot.Lending$.

We also retrieve additional bank-level variables from other regulatory reports. In particular, we use the capital-assets ratio, ROA, and the log of total assets. We use such variables as controls for bank's capitalization, profitability and size in our regressions. We then use balance sheet information for UK NFCs. Data are from Bahaj et al. (2020) based on FAME by BvD. The dataset provides extensive balance sheet data for the universe of UK firms. Importantly, FAME provides information on firm lending relationships with financial intermediaries. This allows us to link NFCs to their banks and to analyse the role of bank international lending on their domestic clients productivity. In line with Bahaj et al. (2020) we only keep active firms and restrict our sample to only include limited liability companies.

¹² 2024 data on the other hand refer to the end of Q1.

¹³ FAME only reports information on secured loans received by firms. See De Marco et al. (2021) for further details.

The focus of this paper is on NFCs productivity growth. As a first proxy we focus on labour productivity, measured by the growth rate of $Sales\ per\ employee$. Then, we calculate the growth rate of total factor productivity by resorting to OLS and to the classical Olley and Pakes (1996) algorithm. To estimate TFP we use real sales as dependent variable. In line with with Bournakis and Mallick (2018), we convert sales from FAME into real values using a 2-digit NACE domestic output industry deflator (2022 = 100) from the Office of National Statistics (ONS). ¹⁴ Capital stock is calculated as the log of fixed assets, that is deflated with the industry invariant Gross fixed capital formation deflator (2022 = 100) (ONS). ¹⁵ Factor labour is calculated as the log the total number of employees. $TFP\ OLS\ (growth\ rate)$ is calculated as the first difference of the residual of an OLS regression.

Since OLS estimation of TFP might provide biased results because of simultaneity between unobserved productivity shocks and inputs, we also followed the algorithm by Olley and Pakes (1996) and calculate TFP OP (growth rate) with their semi-parametric approach. See Appendix B. for details. To do so we extract additional data from FAME. First, we use information on the company status, i.e. active and inactive. We then calculate Investment as the first difference of real fixed assets plus real depreciation, where to obtain real values we use capital asset deflator (ONS), and then transform it in log. Finally, we use the log real cost of sales, where the deflator is the industry invariant Inputs into production of Materials for all manufacturing deflator (rescaled so that 2022 = 100) (ONS). 16 TFP and its growth rate are defined as before. From FAME we also use the ratio of domestic to total turnover, the growth rate of total debt, the log of total assets, firm's age, and the ratio of tangible to total assets as firm-level controls in our main estimates. Our final sample in an unbalanced panel consisting of data from 2018 to 2024 for 12,042 UK NFCs. Each NFC can have multiple bank-relationships. We are able to identify in the firm-bank dataset 17 domestic banks for which data on Foreign\Tot.Lending and G7\Tot.Lending are available and 25 foreign banks. Table A.3 provides summary statistics for the bank-firm level dataset.

3. Results

¹⁴ Retrieved from Industry deflators - Office for National Statistics

¹⁵ Retrieved from Gross fixed capital formation deflator: SA - Office for National Statistics

¹⁶ Retrieved from PPI INDEX INPUT - C_MAT Inputs into production of Materials for all manufacturing, excluding Climate Change Levy 2015=100 - Office for National Statistics

In this section we provide results from several empirical methodologies at both macro and micro level supporting the proposition that cross-border lending by domestic banks has a positive spillover effect for the productivity of domestic NFC borrowers. We first start with a cross-country analysis of the relationship between the internationalization of the domestic banking sector and the growth rate of productivity at country level. We then move to a more granular level, by considering cross-country and cross-industry data from a sample of European economies. Finally, we provide micro-evidence of the positive spillover effect arising from cross-border lending by domestic banks by matching within-country, cross-firm data on UK NFCs with administrative bank-level data for UK banks.

3.1 Cross-country approach

We start our cross-country analysis by estimating the following equation with a classical OLS with country fixed effects:

$$Y_{i,t} = \alpha + \beta_1 International \ Lending_{i,t-1} + \beta_2 Controls_{i,t-1} + \partial_t + \theta_i + \varepsilon_{i,t}$$
 (1)

As the dependent variable, we alternatively use the growth rate of *GDP per hour worked* in the economy, the growth rate of *GDP per hour worked in manuf acturing* and the growth rate of *Multifactor Productivity*. Our main regressor, *International Lending*, is the volume of loans by domestic banks to foreign entities, as defined in section 2, in natural log. Following relevant literature on the determinants of productivity, *Controls* include the *Regulatory Quality index* by the World Bank, to control for the role of institutions and the regulatory environment (Égert 2016), the *Economic Complexity* measure by Hidalgo and Hausmann (2009) to control for the sophistication of the real economy (Ferrarini and Scaramozzino 2016; Basile and Cicerone 2022), *R&D expenses to GDP* and the *Human Capital Index* by the World Bank to take into account investment in education and research in the country (Lucas 1988; Romer 1990; Doraszelski and Jaumandreu 2013). We then expand this benchmark specification by adding *Exports to GDP* and inflows of loans from abroad among the covariates. All independent variables enter the specification with a one-year lag, to mitigate concerns about simultaneity. Year (∂_t) and country fixed effects (θ_t) complete the equation, with a well-behaved error term $(\varepsilon_{t,t})$.

We present both estimations carried out using annual data and non-overlapping threeyears average to take into account persistence of the dependent variable and lags in spill-overs from the financial to the real sector.

In Table 1 we report our main findings from the estimation of equation (1) using the parsimonious specification detailed above. We document a positive and strongly significant coefficient associated to our measure of international lending, with respect to both the growth rate

of *GDP per hour worked* and *Multifactor Productivity*. Results are confirmed when using the growth rate of *GDP per hour worked in manufacturing* as dependent variable and when estimating equation (1) in a collapsed sample over non-overlapping three-years averages. In terms of economic significance of our findings, Table 1 shows that a 1% increase in *International Lending* is associated with an increase in the growth rate of productivity for the entire economy in the range of 0.18-0.20 percentage points. The magnitude of the effect is significantly higher when restricting our focus on manufacturing (0.66-0.74 pp). From a different angle, a one standard deviation increase in *International Lending* would translate in almost a one standard deviation (88% of one standard deviation) increase in the growth rate of *Multifactor Productivity*. Among other regressors, the only one showing significant explanatory power is *R&D expenses to GDP*.¹⁷

[Table 1]

We then move to a more complete specification that takes into account additional determinants of productivity: lending from foreign banks and export (Table 2). We include the inflows of foreign lending to analyse whether it is foreign lending from domestic banks that matters for productivity, or in general a greater financial openness to of the country to international markets. Previous results on the internationalization of the domestic banking sector are confirmed both in significance and magnitude. Interestingly, our findings do not point to a significant role of the inflows of loans from foreign countries on the productivity of the real economy. This finding could be due to the fact that foreign banks in advanced economies mainly target established NFCs at the peak of their growth prospects. On the other hand, domestic banks are better positioned to established relationships with less established firms. This could explain the not significant coefficient associated to the inflows of credit from abroad in our sample that consists only of advanced economies.

[Table 2]

In Appendix C. (tables C.1-C.5) we provide a number of additional results. First, we estimate a fixed effects quantile regression (as in Machado and Silva 2019) since the average coefficient estimated with OLS could hide significant heterogeneities at work. In particular, we

¹⁷ Because of the small number of countries in our sample, cluster robust standard errors could provide biased results, considering that the relevant literature shows that a minimum of 30-40 clusters should be available to perform valid inference (Cameron et al. 2008; and Djogbenou et al. 2019). Hence, we use bootstrap standard errors with 400 replications. Results are fully confirmed and stronger in significance when using the classical cluster robust standard errors.

want to check whether an increase in financial openness only affects productivity of already highly productive countries, or if its effect benefits the entire distribution of countries by productivity. We find that the coefficient does not change much along the entire distribution, neither in magnitude nor in significance, especially when using our collapsed sample. Hence, an increase in crossborder lending by domestic banks is associated with increased productivity at each level of the distribution. Second, we augment our specification by including additional regressors (Z-score of the domestic banking system, financial system deposits-to-GDP, banking system assets-to-GDP, and stock market return) that account for: i) banking sector stability, ii) financial size and development, and iii) profitability of financial markets. Previous results are confirmed also when using such additional explanatory variables. Third, we investigate whether foreign lending by domestic banks produces any crowding-out of investment by the domestic economy, in both tangible and intangible assets. Our results do not support this view. If anything, a greater exposure of banks to foreign economies translates into an acceleration of investment in the intangible component (R&D, patents, workers training, software, etc.), the most relevant one in the era of the knowledge economy (Corrado et al. 2022), although such result is not strong from a statistical perspective.

To determine how an increase in foreign lending affects the evolution of productivity growth over time, we resort to a local projection estimate (as in Jorda' 2005), based on the main specification of column 3 of Table 1. We report the cumulated impulse response function of the annual growth in *Multifactor Productivity* after a 1% increase in foreign lending in Figure 3. It shows an increasing effect over time of foreign lending on productivity, in line with our expectations. In particular, a 1% increase in international lending leads to a 1% aggregate increase in the growth rate of productivity over a seven-year period. In other words, the fact that it takes time for the positive spillover effect to materialize suggest that it involve the transfer of soft information such as best practices and know-how which would take time for financial intermediaries to gather and pass on to NFC customers.

[Figure 3]

Finally, although using lags and a collapsed sample should mitigate reverse causality and endogeneity, the relationship between financial openness and productivity is obviously prone to such concerns. Hence, previous results should be considered more as robust correlations than causal evidence. To make a step forward in that direction, in Table 3 we present a large number of system GMM estimations (as in Blundell and Bond 1998) where the dependent variable is the growth rate of *Multifactor Productivity*. The specifications reported in each column change in terms of variables treated as endogenous and the number of lags used as instruments for the

first-differenced equation. ¹⁸ First, we do this in order to check the sensitivity of our results to the different instruments and lag structure. Second, we reduce in a stepwise manner the number of instruments to mitigate instruments proliferation concerns that may invalidate our analysis (Roodman 2009). Both the AR (2) and the Sargan test on instruments validity are generally rejected, pointing to the appropriateness of our specifications. Our main result on the beneficial role of cross-border lending by domestic banks is confirmed and ranges from a 0.05 to 0.18 p.p. increase in the annual growth rate of *Multifactor Productivity* associated with a 1% increase in foreign lending. Although GMM results do mitigate our concerns on endogeneity, they should be taken with a pinch of salt. Indeed, given the low number of countries in our sample, only in columns 9 and 10 we are able to keep the number of instruments below the number of countries, a rule of thumb that the literature on GMM suggests to follow to get reliable results (Roodman 2009). To do so, we use a principal component analysis applied to the lags of regressors to extract our instruments.

[Table 3]

Although this procedure is rather common and considered adequate (Kapetanios and Marcellino 2010), the excessive manipulation of instruments in our estimates could make our analysis unreliable. To provide more robust results in the next two sections we move to a cross-country, cross-industry and within-country, cross-firm settings where we are able to take

In particular, in columns 1 and 3, all variables are treated as endogenous. In columns 2 and 4, only *Multifactor Productivity* and the log of *International Lending* are treated as endogenous, whereas all the other variables are treated as exogenous. In column 5, all variables are treated as endogenous, the instruments matrix is collapsed, and only three lags of each variable are used as instruments. In column 6, all variables are treated as endogenous, the instruments matrix is collapsed, and only two lags of each variable are used as instruments. In column 7, all variables are treated as endogenous, the instruments matrix is collapsed, a principal component analysis is used to extract instruments. In column 8, all variables are treated as endogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments, a principal component analysis is used to extract instruments. In column 9, only *Multifactor Productivity* and the log of international lending are treated as endogenous, all the other variables as exogenous, the instruments matrix is collapsed, a principal component analysis is used to extract instruments (only first 6 components). In column 10, only *Multifactor Productivity* and the log of international lending as treated as endogenous, all the other variables as exogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments, a principal component analysis is used to extract instruments (only first 6 components).

advantage of greater granularity to investigate our main proposition that cross-border lending by domestic banks has positive spillovers for the real economy.

3.2 Cross-country and cross-industry approach

We now move to the second level of our analysis, using country-sector data on productivity for a subset of European countries. We merge the CompNet dataset with the country level data used in the previous section to investigate whether our results are confirmed when adopting a more granular view. First, we estimate the following OLS regression:

$$Y_{j,i,t} = \alpha + \beta_1 International \ Lending_{i,t-1} + \beta_2 Country \ Controls_{i,t-1} + \beta_3 Sector -$$

$$Country \ Controls_{j,i,t-1} + \partial_{j,t} + \theta_{j,i} + \varepsilon_{i,t}$$
(2)

The dependent variable is the (weighted) average growth rate of real revenues per employees in sector j in country i. As a first step, as regressors we only use the country-level variables used in Table 1. We then augment the specification using other country-sector level variables from CompNet (real investment, a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown). All the variables are country-sector weighted averages. We saturate the regression with different levels of fixed effects: at sector and year; or sector*year ($\partial_{j,t}$); or sector*year ($\partial_{j,t}$) and country*sector ($\theta_{j,i}$) level. See Bighelli et al. (2023) for a similar approach using CompNet data.

In Table 4 we present results from the estimation of equation (2) using only country-level variables as regressors. We do confirm a positive and significant effect for *International Lending* when using sector and year fixed effects (columns 1 and 4) and sector*year fixed effects (columns 2 and 5) using both annual and three-years averaged data. In detail, a 1% increase in cross-border lending by domestic banks translates into an increase in the growth rate of the productivity of the domestic economy in the range 0.3-0.5%, an estimate not far from that obtained in the country-level sample. However, the significance of the coefficient vanishes when using sector*year and country*sector fixed effects. This level of saturation is likely to be too granular for the survival of the statistical significance of country-level data.

[Table 4]

Results are fully confirmed when adding country-sector controls to the specification (Table 5), although this comes at the cost of losing some countries from the analysis when such variables

¹⁹ Weights are population weights from Eurostat, based on the number of firms in a given year, two-digit industry and employment size class.

are not available. However, our sample still comprises the five biggest European economies in the sample. ²⁰ Again, we detect a positive and significant effect for *International Lending* until we introduce sector*year and country*sector fixed effects.

[Table 5]

We perform several system GMM models also in this sample to mitigate concerns about endogeneity. The advantage in this case is that the unit of observation is sector *j* in country *i*, amounting to 70 units against the about 20 countries used in Section 3.1. This should mitigate problems with instruments proliferation, as it is easier to model a specification where the number of instruments is lower than that of the units of observation. Results are reported in Table 6. To limit the number of instruments we treat the lagged dependent variable, all country-level variables, real investment and firm's market share as endogenous, whereas we trat the other variables as exogenous. We also present results using instruments with different lag structures. Again, the AR (2) and Hansen test generally point to the validity of the different specifications. As for the level of fixed effects, since the unit of observation is the country-sector pair, results should be interpreted as when controlling for the country*sector $(\theta_{i,i})$ fixed effect. Time fixed effects complete the specifications. We now always document a positive and significant impact of International Lending on the growth rate of productivity. Hence, the unsignificant coefficients estimated with OLS could be the result of simultaneity or endogeneity in the relationship in question.

[Table 6]

In Appendix D., we present additional results at country-sector level. We show that a higher degree of cross-border lending by domestic banks translates into a reduced presence of zombie firms in the domestic economy. Also, *International Lending* seems to be beneficial for investment in both total and intangible fixed assets. Finally, we show that system GMM results do not depend on treating some variables as exogenous and are confirmed when all regressors are instrumented as endogenous. Overall, cross-country, cross-industry evidence is in line with previous results at cross-country level and confirms the existence of a positive spillover effect arising from cross-border lending by domestic banks on the productivity of their national economy.

3.3 Micro-level evidence from UK non-financial companies

²⁰ When using this specification, the countries in the sample are the following: Belgium, Denmark, France, Germany, Italy, Spain, Sweden, United Kingdom.

Can the macro level findings presented in the previous two sections be confirmed when adopting a micro perspective? We now move to our last level of analysis, gathering micro evidence for UK banks and non-financial companies. The UK is a very well-suited context to study the effect of internationalization of the banking system on the productivity of the real economy, because of the presence of a global financial hub in the country (the City of London) and of its relevant role in cross-border financial markets (see IMF, 2022). Moreover, studying the relationship between cross-border lending by domestic banks and productivity of domestic NFCs at a more granular level allows us to increase the robustness of the findings presented above and makes it easier to disentangle causality and to explore heterogeneities and transmission mechanisms. First, we are interested in investigating whether the posited positive spillover effect applies to cross-border lending in general, or only when it is conducted in advanced economies. If the transmission channel via which lending abroad benefits the domestic economy relates to transfer of best practices from foreign to domestic firms, we expect a greater impact of lending to other advanced economies rather than developing countries. Second, extensive literature shows that exporting firms find it beneficial to couple with banks active in international markets, since the latter are able to transfer information about the destination country and better support the firms in its exporting process (De Bonis et al. 2015; Bronzini and D'Ignazio 2017; Claessens and Van Horen 2021; and Paravisini et al. 2023). While the role of greater support for exporting firms is still important from a policy perspective, our results would somehow be less relevant if they depend only on this channel or if they are at work only for such a subset of firms.

To perform the empirical analysis, we link UK NFCs to the banks with whom they have a secured lending relationship and test if an increased share of foreign to total lending (to NFCs) by UK banks determine an increase in productivity of domestic NFC customers. Since the main focus of the paper is on the international lending activity by *domestic* banks, we initially exclude from the analysis foreign banks, following the Bank of England regulatory classification. However, we also create a dummy for NFCs that have a lending relationship with foreign banks and use it in a separate exercise.

We calculate two main variables of interest at bank-level, Foreign\Tot.Lending and G7\Tot.Lending. Since our hypothesis is linked to the transfer of best practices from foreign to domestic NFCs via banks, both in the numerator and denominator we only consider loans to NFCs. Hence, we exclude lending to sovereigns, households, quasi-sovereigns, etc. that could bias our proxy and not capture adequately the exposure of banks to the real economy in both the origin and destination country. We then estimate the following equation:

$$Y_{f,t} = \alpha + \beta_1 Foreign \setminus Tot. Lending_{b,t} + \beta_2 Bank Controls_{b,t} + \beta_3 Firm Controls_{f,t} + \partial_b + \theta_f + \lambda_{j,z,t} + \varepsilon_{i,t}$$

$$(3)$$

As dependent variable we alternatively use: *i*) the growth rate of turnover per employee, *ii*) the growth rate of TFP calculated with OLS, and *iii*) the algorithm by Olley and Pakes (1996), as described in section 2. As bank-specific controls we use capital over total-assets and ROA. As firm-specific control we use: *i*) lagged domestic turnover over total turnover, *ii*) debt growth rate, *iii*) lagged total assets (log), *iv*) age, and *v*) lagged tangible assets over total assets. We estimate several specifications using different levels of saturation, with the maximum one at bank (∂_b), firm (θ_f) and 2-digits industry*year*zip code ($\lambda_{j,z,t}$) level. The inclusion of industry-location-time fixed effects allows us to capture shocks hitting specific industries in specific cities in a certain year and to control for credit demand. Indeed, as shown by Degryse et al. (2019), this methodology works at least as well as widely used methodologies identifying supply only from firms with multiple bank relationships.

In our first exercise, we estimate the impact of *Foreign\Tot.Lending* on the growth rate of client's productivity. Results are presented in Table 7, where in columns 1-3 the dependent variable is the growth rate of turnover per employee, in columns 4-6 the dependent variable is the growth rate of TFP calculated with the traditional OLS, while in columns 7-9 the dependent variable is the growth rate of TFP calculated following Olley and Pakes (1996). In columns 1, 4 and 7 we only use firm and bank fixed effects. We then move to firm, bank, industry*year and zip code*year fixed effects in columns 2, 5 and 8. Finally, we reach the higher level of saturation in columns 3,6 and 9. While the coefficient associated to *Foreign\Tot.Lending* is generally positive, it is statistically significant only in one specification. Overall, it does not seem that an increase in the orientation of UK banks to lend to foreign NFCs affects in any way the productivity performance of their UK clients, contrary to the country and sector-country level results reported in sections 4.1 and 4.2.

[Table 7]

Results drastically change when we focus on lending to foreign NFCs located in advanced economies (*G7\Tot.Lending*) as our main regressor (Table 8). In this case we always document a positive and statistically significant effect. In particular, a 1% increase in the ratio of lending to NFCs in non-UK G7 economies to total lending to NFCs translates into an increase of the growth rate of sales per employee in the range 0.04-0.09 p.p., and in the growth rate of TFP between 0.04 and 0.1 p.p. when calculated with OLS, 0.02- 0.04 p.p. when calculated following Olley and Pakes (1996). Hence, our findings point to a positive spillover effect only when cross-border lending activity of domestic banks is in advanced economies. This is in line with our proposition

that the positive spillover effect is based on the sharing of business-relevant information. If the improvement of clients' productivity depends on the transfer of best practices and knowledge from foreign business environments, then it is reasonable to expect that such beneficial effects are stronger when banks have a deeper presence in highly productive and technologically intensive countries. Our results suggest that banks that operate in non-UK G7 economies create relationships with firms at the productivity frontier, are able to acquire soft information and management best practices from them and to transfer them at home to domestic clients.

[Table 8]

Does this pattern emerge also when UK NFCs have a lending relationship with a foreign bank? In Table 9 we replicate the previous estimation by replacing the main regressor with a dummy taking value 1 for NFCs that at time t have some outstanding credit from a foreign bank, according to the Bank of England regulatory classification. Our results show that, if anything, such firms experience a decline in productivity. However, we estimate significant results only when the dependent variable is the growth rate of turnover per employee. This result is consistent with the proposition that foreign banks tend to focus on large and established NFCs less likely to benefit from the posited positive information spillover effect in that they are already close or at the productivity frontier.

[Table 9]

We test the sensitivity of our results to several robustness checks, as reported in Appendix E. We first change the fixed effects structure in equation (3) by using: i) firm and zip*industry fixed effects, ii) bank, firm, year and zip*industry fixed effects, and iii) firm, year*industry and bank*zip fixed effects. The last specification allows us to control for banks systematically targeting the best performers in a certain city. We show that our results do not depend on the specific structure of fixed effects used in Table 8. Second, we add bank size measure by its total assets (in log) among controls. Third, we estimate several system GMM specifications. Previous results are confirmed, with an increase in $G7 \setminus Tot$. Lending having a positive impact on productivity, greater than that of $Foreign \setminus Tot$. Lending. However, since the Hansen J-test casts doubts on the validity of instruments, we finally move to system GMM with the dependent variable in level in place of a growth rate. Previous results are confirmed.

To further control for endogeneity in our estimates, we follow Kneer and Raabe (2024) and resort to a Bartik/shift-share instrument to perform a 2SLS estimation. This allows us to isolate exogenous variation in banks' foreign lending. The instrument is constructed by combining predetermined bank-level exposure shares with aggregate foreign lending shocks, following the

classic shift-share design which has been widely used in the econometric literature, see for instance Autor et al. (2016). The instrument has the following form:

$$Foreign \ Lending_{bt} = \sum_{c=1}^{C} (share_{cb} * \ UK \ Foreign \ Lending_{ct})$$
 (4) with $t \geq 2018$ and $share_{cb} = \frac{foreign \ lending_{cbt}}{foreign \ lending_{ct}}$ with $t = 2014Q4$.

First, we calculate the $share_{cb}$, i.e. the historical share of loans to country c from the UK banking system that is made by bank b, calculated as of Q4 of 2014.21 In a second step, we multiply the historical share with total loans from UK banks to country c (UK Foreign Lending_{ct}) in later years. Hence, the instrument uses the historical distribution of the stock of foreign loans to some country c across UK banks to allocate loans to country c in subsequent years across UK banks. Finally, for each bank b in year t we obtain a measure of its aggregate foreign lending by summing across loans to all countries c. We use this instrument in a 2SLS regression as an instrument for our main regressors (Foreign\Tot. Lending and G7\Tot. Lending). When used as an instrument for Foreign\Tot. Lending, c includes all foreign countries. On the other hand, when used as an instrument for G7\Tot. Lending, c includes only G7 economies excluding the UK. The rationale of the instrument is that the initial share has predictive power for the subsequent allocation of foreign loans from UK domestic banks because of the long-term planning underpinning decision about their presence in foreign countries. At the same time, we expect the instrument to satisfy the exogeneity condition with respect to the productivity growth of UK NFCs. since it is unrealistic to consider that outflows of loans from the entire UK banking system depend on the change in productivity by domestic companies. In a similar fashion, we expect exogeneity to hold also for the first component of the instrument, the historical percentage of UK loans to a specific country c made by bank b. In interrogating the validity of our Bartik/shift share design we follow closely the advice of Borusyak et al. (2025), who frame these discussions around shift and share exogeneity. Although we think that both our shifts and shares are likely to be exogenous, let us for a moment focus on the exogeneity of shares. This is equivalent to assuming banks 2014 foreign lending shares are plausibly exogenous to future firm productivity growth, after conditioning on appropriate fixed effects and controls. Or to put it another way, if the post-2018 foreign lending shock hadn't occurred, firms attached to high-exposure banks vs. low-exposure banks would have had parallel TFP growth trajectories.

We take several steps to bolster the credibility of the share exogeneity assumption. First, as mentioned we include a rich set of fixed effects to absorb potential confounds. In our baseline

²¹ This is the first end-of-year figure available in COREP data for foreign lending.

specification we include firm fixed effects, year fixed effects, and industry-year fixed effects. Including the fixed effects mean that the instrument's identifying variation comes from within-firm changes, comparing firms in the same industry-year who have different exposure via their banks to foreign lending shocks.

Another key identification assumption is that the aggregate foreign lending shocks themselves are plausibly exogenous to individual banks and firms. We assume that the total post-2018 increase in UK lending to a given foreign country (G7 country) is driven by country-specific economic conditions or global financial factors – not by the idiosyncratic credit demand or performance of any one UK bank or its client firms. This is reasonable given the scale of for example G7 economies and the breadth of UK banking engagement in each: for example, if UK lending to the US surged after 2018 due to US economic growth, that shock is unlikely to be caused by any single British bank or a particular subset of UK firms who are clients of British banks. In our data, each G7 country's credit shock is distributed across many banks, diluting the influence of any one bank's behaviour on the aggregate shift. Thus, we treat the country-level lending shifts as externally given push factors. Combined with the use of historical (pre-2018) exposure weights, this helps satisfy the exclusion restriction for our IV.

Results are reported in Table 10 and 11. In the first stage, the instrument has a strong predictive power over the main regressors, with its F-statistics comfortably passing the Staiger and Stock (1997) rule of thumb (F-statistics higher than 10) and Stock and Yogo (2002) thresholds on weak instruments. Second stage results fully confirm our previous findings, with Foreign\Tot.Lending showing a positive although rarely significant coefficient and G7\Tot.Lending associated with a positive and strongly significant one. Results are confirmed also in magnitude. The Bartik IV estimate of the impact of foreign lending exposure on TFP does not change much when adding firm, time, and industry-year FE. This suggests that the baseline estimate was not biased by omitted factors that the FE later controlled. In other words, once basic controls were in place, the remaining bias was minimal – a sign that the instrument was already isolating the causal variation reasonably well. The shares also seem uncorrelated with major confounders (consistent with the exogeneity assumption).

[Tables 10 and 11]

As an additional exercise to mitigate concerns about endogeneity, we re-estimate our main equation on a subsample of firms operating in sectors that performed particularly badly in the UK compared with other G7 economies, in the years before our firm-level data become available. In particular, we examine country-sector data from the OECD and the US Bureau and Labour Statistics in the period 2014-2017 to select the macro-sector in which the UK showed the

highest distance from other G7 economies in terms of its growth rate of GDP per hour worked. We find the macro-sector consisting of sections G, H and I of the SIC classification performed particularly poorly in the UK.²² Figure 4 shows that while the UK experience an average annual growth rate of 0.2% in this macro-sector, the *i*) US and *ii*) Canada, France, Germany and Italy performed significantly better (1 and 1.2% respectively), while data for Japan are not available.²³

[Figure 4]

We estimate equation (3) in the subset of UK firms operating in these sector and present results in Table 12.²⁴ The rationale of this exercise is that if we document a positive effect of foreign lending by banks on UK NFCs' productivity, this cannot be ascribed to firms' endogenous patterns, since macro data show that these sectors performed very poorly in the UK compared to other advanced economies in the years immediately before 2018. On the contrary, it would support our hypothesis that the positive spillover effects are based on the information-sharing channel where domestic banks pass on knowledge on relevant best business practices gathered from lending relationships with NFC borrowers in advanced economies. Our findings seem to corroborate this view. We show that even when focusing on the subset of NFCs operating in this macro sector, greater exposure towards other advanced economies for UK banks translated into improved productivity for their clients.

[Table 12]

Finally, we explore potential heterogeneities in the relationship of interest resorting to interactive specifications. First, we interact $G7\Tot.Lending$ with a dummy identifying exporting and non-exporting firms to investigate whether our findings only depend on better support by internationalized banks to exporting NFCs. Then, we interact the main regressor with a dummy

²² Section G comprises firms operating in wholesale and retail trade, and repair of motor vehicles and motorcycles; section H has firms operating transportation and storage; section I comprises firms in accommodation and food service activities. We are not able to use a more granular classification since OECD data are at macro-sector level and considers sections G, H and I as part of the same one. We complement this data with information coming from the US Bureau and Labour Statistics since the OECD does not report productivity data at macro-sector level for the US.

²³ According to our data, the macro-sector consisting of sections G+H+I was the second worst in the UK vs other G7 economies comparison. The worst performing one was construction, but since our firm-level dataset only has few firms in that sector we prefer considering the much more populated one. Moreover, sections G+H+I were also the worst performing in the years 2018-2024.

²⁴ Since this estimation is carried on a subset of sectors, the fixed effects we use are different from the main table because we prefer not including industry FE in any form to avoid removing too much variability.

taking value 1 for long-lasting NFCs-banks lending relationships (more than 4 years) and 0 for newer ones (at most 4 years) to check whether the beneficial productivity effects show up immediately after the NFC starts a lending relationship with a bank lending abroad or whether such effect takes time to consolidate. In Figure 5 and 6 we plot marginal effects estimated from such interactions.

[Figures 5 and 6]

We do not find a significant difference in the effect for exporting and non-exporting firms. Having a relationship with an internationalized bank is beneficial to both sets of firms. Also, positive spillover effect materializes in the early years since the start of a firm-bank relationship. These results also support the view that the positive spillover effect is due to the posited information-sharing channel.

4. Conclusions

In this paper we empirically investigated whether the international lending activity of the domestic banking sector matters for the productivity of the domestic real economy. We investigated this question under a variety of approaches, using cross-country, cross-country / cross-sector and within-country / cross-level panel estimations.

Our results point to a beneficial role of banking sector internationalisation on the productivity of the domestic real economy. Using cross-country panel data from around 20 advanced economies from 1998 to 2019, we find that a 1% increase in foreign lending by domestic banks is associated with an increase in the growth rate of productivity of the domestic economy in the range of 0.18-0.74 p.p., based on which dependent variable is used. This effect reinforces over time and leads to a cumulated increase in growth rate of productivity of around 1% in a horizon of seven years. Results, that come from OLS estimates, are confirmed when estimating several system GMM specifications and are stable throughout the entire distribution of countries by productivity.

Positive effects on productivity emerge also when using cross-country / cross-sector data from a sample of European economies, and when moving to firm-level evidence from UK non-financial companies, a framework that enables us to conduct additional robustness tests on endogeneity (Bartik IV) and to better test transmission mechanisms. In particular, first we document that the benefits to domestic NFC borrowers mainly arise when their banks increase the share of their lending activity to firms in foreign G7 countries. Second, we find that the positive role of the foreign lending activity of domestic banks on their domestic NFC borrowers not only depends on export support, as shown by previous literature, but emerges also in the sample of non-exporting firms.

Finally, we document that results are slightly more intense at an early stage of the bank-firm relationship. In contrast, we find no evidence that lending by foreign banks to domestic NFCs is associated with productivity improvements.

Taken together, our results indicate that countries would benefit from developing a banking sector that is open to international markets and that the positive effects of foreign lending on domestic productivity can be the result of positive information spillovers, whereby internationally active domestic banks use the intelligence gathered by lending to foreign NFCs to better screen and monitor domestic NFCs, especially to the benefit of those with a potential for productivity improvements.

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Table 1. Effect of bank international lending on domestic productivity, parsimonious specification.

	(1)	(2)	(3)	(4)	(5)	(6)		
	. ,	Yearly observatio		Collapsed (3-years averages)				
	GDP per hour worked	•	Multifactor Productivity	GDP per hour worked	Manufacturing	Multifactor Productivity		
VARIABLES	(growth rate)	per hour worked (growth rate)	(growth rate)	(growth rate)	per hour worked (growth rate)	(growth rate)		
International Lending (log, lag)	0.1866*** (0.0707)	0.6603*** (0.2274)	0.1784*** (0.0665)	0.1843*** (0.0639)	0.7481*** (0.1884)	0.2006*** (0.0710)		
Regulatory Quality (lag)	0.4964 (0.5768)	-1.9179 (1.4150)	-0.0990 (0.4462)	0.3595 (0.4765)	0.4370 (2.0885)	-0.1264 (0.5710)		
Economic Complexity (lag)	0.0599 (0.9185)	5.7327* (3.2152)	-0.1759 (0.9557)	-0.4298 (1.5049)	3.0659 (3.5556)	-0.1162 (1.2980)		
R&D_Expenditure (%GDP, lag)	1.2286* [*]	0.6547	0.9092**	1.5839* [*] *	2.9501* [*] *	1.3559* [*] **		
Human Capital Index	(0.4955) 1.3891 (2.4035)	(1.0848) -4.1094 (6.2902)	(0.4446) 1.0778 (2.3101)	(0.5068) -0.0953 (2.3094)	(1.1374) -0.8402 (7.5841)	(0.4056) 0.9560 (2.3176)		
Constant	Yes	Yes	Yes	Yes	Yes	Yes		
Country FE	Yes	Yes	Yes	Yes	Yes	Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	325	265	321	118	95	117		
R-squared	0.3474	0.4100	0.4524	0.4290	0.5886	0.4975		
Number of countries	21	16	20	21	16	20		

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Effect of bank international lending on domestic productivity, extended specification.

	(1)	(2)	(3)	(4)	(5)	(6)		
		early observation	S	Collapsed (3-years averages)				
VARIABLES	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)	ν.Ο	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)		
International Lending (log, lag)	0.2001** (0.0920)	0.6975*** (0.2370)	0.1656** (0.0806)	0.1996*** (0.0693)		0.1815** (0.0818)		
Regulatory Quality (lag)	0.7636 (0.6706)	-2.0840 (1.9607)	0.1389 (0.5233)	1.0663* (0.6028)		0.4642 (0.4718)		
Economic Complexity (lag)	-0.1481 (0.9731)	5.4027 (3.5550)	-0.4070 (0.8883)	-0.7096 (1.3649)		-0.1935 (1.0620)		
R&D_Expenditure (%GDP, lag)	1.3057** (0.5772)	1.1882 (1.6262)	0.8555* (0.4920)	1.9651*** (0.6042)	3.0209***	1.4980*** (0.4933)		
Human Capital Index	1.1619 (2.9694)	-8.5894 (9.9706)	2.4720 (2.3590)	0.2904 (3.3096)	•	3.3060 (3.0916)		
Inflows Loans (log, lag)	-0.0761 (0.1511)	-0.2432 (0.2754)	-0.1716 (0.1634)	-0.2260 (0.2259)	-0.3519	-0.2660 (0.1696)		
Exports (%GDP, lag)	-0.0663 (2.0906)	-1.6998 (7.7051)	1.6349 (1.9252)	0.1052 (1.9145)	-0.1315 (5.4379)	1.7261 (1.8762)		
Constant	Yes	Yes	Yes	Yes	· · · · · · · · · · · · · · · · · · ·	Yes		
Country FE	Yes	Yes	Yes	Yes		Yes		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	301	245	295	105	85	104		
R-squared	0.3326	0.4131	0.4632	0.3999	0.5824	0.5402		
Number of countries	21	16	20	21	16	20		

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Effect of bank international lending on domestic productivity, sys-GMM. Collapsed sample (3-years averages).

Dependent: Multifactor Productivity (growth rate).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Multifactor Productivi	ty									
(growth rate, lag)	0.263***	0.241***	0.169**	0.203***	0.075	0.086	0.259*	0.182	-0.035	-0.247
	(0.077)	(0.060)	(0.068)	(0.067)	(0.165)	(0.216)	(0.136)	(0.170)	(0.241)	(0.510)
International Lending (log	g,									
lag)	0.048#	0.060*	0.056*	0.070**	0.159*	0.171**	0.095#	0.103#	0.158*	0.187**
	(0.030)	(0.030)	(0.029)	(0.032)	(0.084)	(0.072)	(0.057)	(0.064)	(0.090)	(0.084)
Regulatory Quality (lag)	0.124	0.138	0.139	0.139	0.311	0.262	0.482	0.868	0.272	0.354
5 5 7 67	(0.138)	(0.156)	(0.181)	(0.194)	(0.476)	(0.587)	(0.334)	(0.589)	(0.285)	(0.390)
Economic Complexity (lag)	-0.055	-0.070	-0.077	-0.089	0.461	-0.253	0.089	0.449	-0.192	-0.232
	(0.102)	(0.103)	(0.108)	(0.107)	(0.447)	(0.443)	(0.362)	(0.525)	(0.195)	(0.205)
R&D_Expenditure (%GDF	⊃, ` ´	,	, ,	,	, ,	,	,	, ,	, ,	, ,
lag)	0.397***	0.422***	0.487***	0.492***	0.235	0.635**	0.367	0.033	0.700**	0.818**
-,	(0.117)	(0.119)	(0.112)	(0.111)	(0.353)	(0.285)	(0.369)	(0.549)	(0.263)	(0.316)
Human Capital Index	-0.110	-0.138	-0.239	-0.273	-0.236	-0.626	-0.479	-0.442	-0.467	-0.520
	(0.226)	(0.253)	(0.234)	(0.245)	(0.748)	(0.767)	(0.342)	(0.446)	(0.483)	(0.494)
Inflows Loans (log, lag)			0.023	0.018	-0.263*	-0.301**	-0.150	-0.224	0.009	0.014
			(0.040)	(0.042)	(0.129)	(0.140)	(0.125)	(0.178)	(0.057)	(0.069)
Exports (%GDP, lag)			-0.138	-0.145	-0.566	-0.597	-0.943#	-1.002	-0.276	-0.343
			(0.131)	(0.136)	(0.719)	(0.509)	(0.588)	(0.863)	(0.195)	(0.259)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117	117	104	104	104	104	104	104	104	104
Prob>AR(2)	0.697	0.680	0.395	0.423	0.321	0.380	0.483	0.405	0.276	0.129
Prob>Sargan	0.162	0.0314	0.116	0.0186	0.134	0.376	0.0676	0.00961	0.0436	0.196
N. of instruments	113	65	104	64	38	30	41	30	18	18
Number of countries	20	20	20	20	20	20	20	20	20	20

NOTES: Period 1998-2019. Columns 1 and 3: all variables treated as endogenous. Columns 2 and 4: the lagged value of Multifactor productivity and the log of international lending as treated as endogenous, all the other variables as exogenous. Column 5: all variables are treated as endogenous, the instruments matrix is collapsed, only three lags of each variable are used as instruments. Column 6: all variables are treated as endogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments. Column 7: all variables are treated as endogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments. Column 8: all variables are treated as endogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments, a principal component analysis is used to extract instruments. Column 9: the lagged value of Multifactor productivity and the log of international lending as treated as endogenous, all the other variables as exogenous, the instruments

matrix is collapsed, a principal component analysis is used to extract instruments (only first 6 components). Column 10: the lagged value of Multifactor productivity and the log of international lending as treated as endogenous, all the other variables as exogenous, the instruments matrix is collapsed, only two lags of each variable are used as instruments, a principal component analysis is used to extract instruments (only first 6 components) Prob>AR(2) reports the p-value of a AR test for second order autocorrelated disturbances in the first differenced equations. Prob>Sargan reports the p-value of a Sargan test where the null hypothesis is instrument validity. Standard errors in parentheses are clustered at country level. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15

Table 4. Effect of bank international lending on country-sector level productivity.

Dependent: Real revenue per employee (growth rate).

	(1)	(2)	(3)	(4)	(5)	(6)
	<u>Year</u>	ly observa	<u>tions</u>	Collapsed	(3-years ave	erages)
VARIABLES		Real rev	enue per e	mployee (gr	owth rate)	
International Lending (log, lag)	0.262**	0.270***	-0.175	0.503***	0.506***	0.120
	(0.106)	(0.100)	(0.117)	(0.111)	(0.113)	(0.209)
Regulatory Quality (lag)	0.376	0.408	-2.668	1.360	1.428	-1.791
	(0.944)	(0.994)	(1.622)	(0.907)	(0.928)	(2.034)
Economic Complexity (lag)	-0.926	-0.968	-2.590	-1.281	-1.315	0.911
	(0.723)	(0.763)	(2.595)	(0.781)	(0.830)	(3.790)
R&D_Expenditure (%GDP, lag)	1.592**	1.585**	-2.149**	2.014***	1.999***	-0.968
	(0.646)	(0.664)	(1.059)	(0.663)	(0.688)	(1.381)
Human Capital Index	-0.180	-0.184	0.540	-0.894	-0.912	0.424
	(1.253)	(1.326)	(8.086)	(1.378)	(1.439)	(9.329)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Time FE	No	Yes	Yes	No	Yes	Yes
Country*Sector FE	No	No	Yes	No	No	Yes
Observations	1,446	1,437	1,437	503	494	494
R-squared	0.203	0.219	0.310	0.295	0.256	0.488
Number of countries	12	12	12	12	12	12
Number of sector-countries	106	106	106	106	106	106

NOTES: Period 1998-2019. Standard errors clustered at sector-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effect of bank international lending on country-sector level productivity. Additional controls. Dependent: Real revenue per employee (growth rate).

	(1)	(2)	(3)	(4)	(5)	(6)			
	<u>Ye</u>	arly observa	ations	<u>Collap</u>	sed (3-years	averages)			
VARIABLES	Real revenue per employee (growth rate)								
International Lending (log, lag)	0.854***	0.849**	-0.288	1.408***	1.416***	-0.454			
	(0.298)	(0.323)	(0.582)	(0.431)	(0.438)	(1.332)			
Regulatory Quality (lag)	-1.723	-1.501	-6.446**	-3.438*	-3.295*	-7.466**			
	(1.583)	(1.555)	(2.981)	(1.802)	(1.809)	(3.619)			
Economic Complexity (lag)	-3.161***	-3.085***	-11.694**	-5.236***	-5.211***	-14.366**			
	(1.057)	(1.109)	(4.819)	(1.399)	(1.411)	(5.529)			
R&D_Expenditure (%GDP, lag)	2.513***	2.354***	-3.819*	3.996***	3.923***	0.391			
	(0.642)	(0.665)	(1.935)	(0.892)	(0.902)	(2.154)			
Human Capital Index	5.214***	5.197***	-9.170	6.971***	6.825***	5.226			
	(1.791)	(1.891)	(23.066)	(2.215)	(2.256)	(26.871)			
Constant	Yes	Yes	Yes	Yes	Yes	Yes			
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes			
Time FE	Yes	Yes	Yes	Yes	Yes	Yes			
Sector*Time FE	No	Yes	Yes	No	Yes	Yes			
Country*Sector FE	No	No	Yes	No	No	Yes			
Additional sector-countries controls	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	966	957	957	334	325	325			
R-squared	0.288	0.317	0.394	0.408	0.388	0.562			
Number of countries	8	8	8	8	8	8			
Number of sector-countries	70	70	70	70	70	70			

NOTES: Period 1998-2019. Additional sector-country controls are real investment, a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. All sector-country controls are sector-country specific weighted averages. Standard errors clustered at sector-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Effect of bank international lending on country-sector level productivity. System-GMM on collapsed sample. Dependent: Real revenue per employee (growth rate).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real revenue per employee (growth rate, lag)	-0.065	-0.065	-0.074	-0.066	-0.080	-0.081
, 0,	(880.0)	(880.0)	(0.086)	(880.0)	(0.085)	(0.085)
International Lending (log, lag)	1.476*	1.459*	1.466*	1.516*	1.481*	1.459*
	(0.752)	(0.753)	(0.760)	(0.771)	(0.746)	(0.767)
Regulatory Quality (lag)	-3.482	-3.495	-3.411	-3.436	-3.229	-3.095
	(2.201)	(2.191)	(2.163)	(2.207)	(2.232)	(2.253)
Economic Complexity (lag)	-6.427***	-6.449***	-6.404***	-6.359***	-6.251***	-6.146***
	(1.416)	(1.408)	(1.408)	(1.420)	(1.462)	(1.521)
R&D_Expenditure (%GDP, lag)	4.645***	4.650***	4.615***	4.618***	4.487***	4.368***
	(1.087)	(1.082)	(1.078)	(1.082)	(1.121)	(1.138)
Human Capital Index	6.019**	6.017**	5.982**	6.013**	5.896**	5.815**
·	(2.526)	(2.527)	(2.533)	(2.537)	(2.553)	(2.608)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional sector-countries controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	325	325	325	325	325	325
Prob>AR(2)	0.280	0.279	0.269	0.291	0.263	0.262
Prob>Hansen	0.829	0.552	0.321	0.494	0.156	0.156
N. of instruments	89	81	75	79	68	66
Number of sector-countries	70	70	70	70	70	70

NOTES: Period 1998-2019. Additional sector-country controls are real investment, a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. All country-level variables are treated as endogenous, the lagged dependent variable, real investment and firm's market share are treated as endogenous, the other variables as predetermined. Column 1: all available lags of each variable are used as instruments. Column 2: all available lags of the country-level variables are used as instruments, only the most three recent lags of the sector-country level variables are used as instruments. Column 3: only the most three recent lags of each variable are used as instruments. Column 4: all available lags of the country-level variables are used as instruments, only the most two recent lags of the sector-country level variables are used as instruments. Column 5: only the most two recent lags of each variable are used as instruments. Column 6: only the most two recent lags of country-level variables are used as instruments, only the most recent lag of sector-country level variables is used as instruments. Prob>AR(2) reports the p-value of a AR test for second order autocorrelated disturbances in the first differenced equations. Prob>Hansen reports the p-value of a Hansen test where the null hypothesis is instrument validity. Standard errors in parentheses are clustered at country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Effect of bank lending to foreign NFCs on different measures of domestic NFCs' productivity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales pe	er employee ((growth rate)	<u>TFP</u>	OLS (growth	n rate)	TFP OP (growth rate)		
VARIABLES									
Foreign/Tot. Lending	0.0174	0.0333	0.0148	0.0193	0.0455*	0.0227	0.0101	0.0188	-0.0001
	(0.0124)	(0.0219)	(0.0225)	(0.0134)	(0.0239)	(0.0255)	(0.0069)	(0.0132)	(0.0141)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry*Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
ZIP*Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry*ZIP*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	44,214	44,213	38,385	44,135	44,134	38,316	41,335	41,334	35,638
R-squared	0.3846	0.3846	0.5704	0.3171	0.3172	0.5204	0.3845	0.3848	0.5618

Table 8. Effect of bank lending to foreign G7 NFCs on different measures of domestic NFCs' productivity.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0.0357** (0.0168)	0.0854** (0.0382)	0.0678*	0.0373** (0.0189)	0.1012** (0.0404)	0.0735* (0.0436)	0.0177* (0.0095)	0.0432* (0.0229)	0.0155 (0.0257)
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
No	No	Yes	No	No	Yes	No	No	Yes
44,214	44,213	38,385	44,135	44,134	38,316	41,335	41,334	35,638
0.3846	0.3847	0.5704	0.3171	0.3172	0.5205	0.3845	0.3849	0.5618
	0.0357** (0.0168) Yes Yes Yes Yes No Yes Yes No 44,214	Sales per employee (green) 0.0357** 0.0854** (0.0168) (0.0382) Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes Yes Yes Yes Yes Yes No No 44,214 44,213	Sales per employee (growth rate) 0.0357** 0.0854** 0.0678* (0.0168) (0.0382) (0.0402) Yes Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes Yes Yes No Yes Yes No Yes Yes No No No Yes 44,214 44,213 38,385	Sales per employee (growth rate) TFP 0.0357** 0.0854** 0.0678* 0.0373** (0.0168) (0.0382) (0.0402) (0.0189) Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes No Yes Yes No Yes Yes Yes No Yes No Yes No Yes No No Yes No 44,214 44,213 38,385 44,135	Sales per employee (growth rate) TFP OLS (growth rate) 0.0357** 0.0854** 0.0678* 0.0373** 0.1012** (0.0168) (0.0382) (0.0402) (0.0189) (0.0404) Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No No Yes Yes No No No No 44,214 44,213 38,385 44,135 44,134	Sales per employee (growth rate) D.0357** 0.0854** 0.0678* 0.0373** 0.1012** 0.0735* (0.0168) (0.0382) (0.0402) (0.0189) (0.0404) (0.0436) Yes Yes Yes Yes Yes No Yes Yes Yes No Yes Yes No Yes No Yes Yes No No Yes No No No Yes No No Yes 44,214 44,213 38,385 44,135 44,134 38,316	Sales per employee (growth rate) TFP OLS (growth rate) TFF OLS (growth rate) TFF OLS (growth rate) 0.0357** 0.0854** 0.0678* 0.0373** 0.1012** 0.0735* 0.0177* (0.0168) (0.0382) (0.0402) (0.0189) (0.0404) (0.0436) (0.0095) Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes Yes Yes No No Yes No No Yes No <	Sales per employee (growth rate) TFP OLS (growth rate) TFP OP (growth rate) 0.0357** 0.0854** 0.0678* 0.0373** 0.1012** 0.0735* 0.0177* 0.0432* (0.0168) (0.0382) (0.0402) (0.0189) (0.0404) (0.0436) (0.0095) (0.0229) Yes Yes Yes Yes Yes Yes Yes No Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No Yes Yes No Yes Yes Yes No Yes Yes No Yes Yes Yes No No Yes No No No<

Table 9. Effect of having a lending relationship with a foreign bank on different measures of domestic NFCs' productivity.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sales p	<u>er employee</u>	TFP OLS	(growth rate)	TFP OP (g	growth rate)
	(gro	wth rate)				
VARIABLES						
International Bank (dummy)	-1.2568*	-1.5833**	-0.5065	-1.0707	-0.0536	-0.3819
	(0.6908)	(0.7299)	(0.7420)	(0.7848)	(0.4040)	(0.3568)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Industry*Time FE	No	Yes	No	Yes	No	Yes
ZIP*Time FE	No	Yes	No	Yes	No	Yes
ZIP*Industry FE	Yes	No	Yes	No	Yes	No
Observations	44,214	44,213	38,385	44,135	44,134	38,316
R-squared	0.3846	0.3846	0.5704	0.3171	0.3172	0.5204

Table 10. Effect of bank lending to foreign NFCs on different measures of domestic NFCs' productivity. 2SLS regression with Bartik instrument.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales pe	r employe	ee (growth rate)	TFP (OLS (growt	h rate)	TFP O	P (growth	n rate)
VARIABLES									
Foreign/Tot.Lending	0.021	0.008	0.010#	0.014#	0.009	0.011*	0.013#	0.006	0.004
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
ZIP*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Bartik Instrument	***	***	***	***	***	***	***	***	***
Instrument first stage F-stat	142.717	29.143	28.689	142.444	29.053	28.597	138.465	27.498	26.967
Observations	48,496	44,785	42,328	48,411	44,708	42,257	45,391	41,912	39,598

NOTES: Period 2018-2024. The instrument used in the first stage is the Bartik instrument defined in equation (). We report its significance and the Kleibergen-Paap rkWald F statistic to evaluate instrument relevancy and strength. Standard errors in parentheses are clustered at firm and year level. Firm controls: lagged domestic/tot. turnover, debt growth rate, lagged tot. assets log, age, lagged tangible/tot.assets. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table 11. Effect of bank lending to foreign G7 NFCs on different measures of domestic NFCs' productivity. 2SLS regression with Bartik instrument.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales ı	oer emplo	yee (growth						
		<u>rate</u>	<u>)</u>	<u>TFP</u>	OLS (growt	h rate)	TFP C	OP (growt	h rate)
VARIABLES									
G7/Tot. Lending	0.055*** (0.02)	0.022* (0.01)	0.023** (0.01)	0.020** (0.01)	0.022* (0.01)	0.025** (0.01)	0.017***	0.013* (0.01)	0.011# (0.01)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
ZIP*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Instrument significance	***	***	***	***	***	***	***	***	***
Observations	48,490	44,783	42,326	48,405	44,706	42,255	45,385	41,910	39,596
Instrument F-stat	253.666	36.429	36.224	253.043	36.312	36.101	249.378	33.211	32.899

NOTES: Period 2018-2024. The instrument used in the first stage is the Bartik instrument defined in equation (). We report its significance and the Kleibergen-Paap rkWald F statistic to evaluate instrument relevancy and strength. Standard errors in parentheses are clustered at firm and year level. Firm controls: lagged domestic/tot. turnover, debt growth rate, lagged tot. assets log, age, lagged tangible/tot.assets. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table 12. Effect of bank lending to foreign G7 NFCs on different measures of domestic NFCs' productivity. Subsample of SIC sections G, H and I.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sales per e	mployee (growth				
		<u>rate)</u>	TFP OL	S (growth rate)	TFP OP (growth rate
VARIABLES						
G7/Tot.Lending	0.0201	0.1110*	0.0468*	0.1799***	0.0338**	0.0919*
	(0.0258)	(0.0666)	(0.0260)	(0.0684)	(0.0167)	(0.0489)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes
ZIP*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3814	0.3815	0.3295	0.3298	0.3472	0.3475
Observations	15,162	15,138	14,821	15,162	15,138	14,821

Figure 1. Country foreign claims as a percentage of total foreign claims by year.

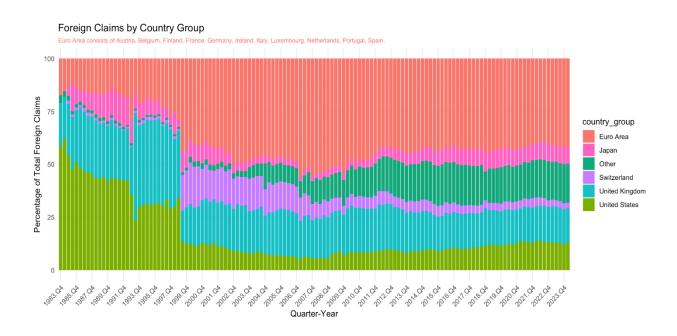


Figure 2. Average growth rate of productivity variables by year.

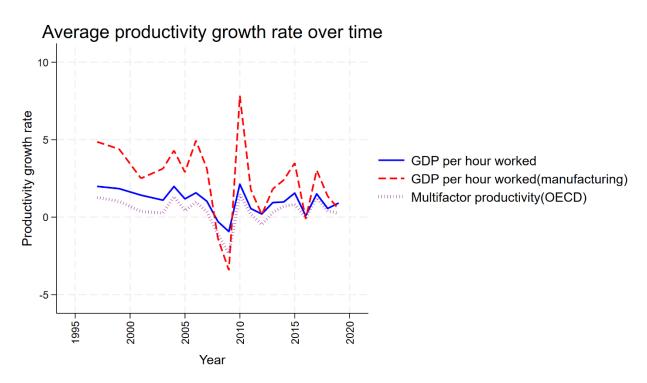
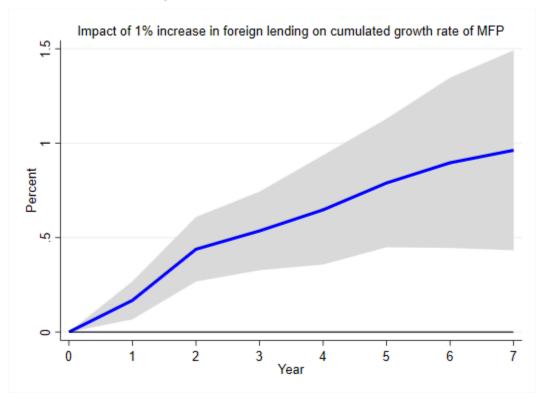
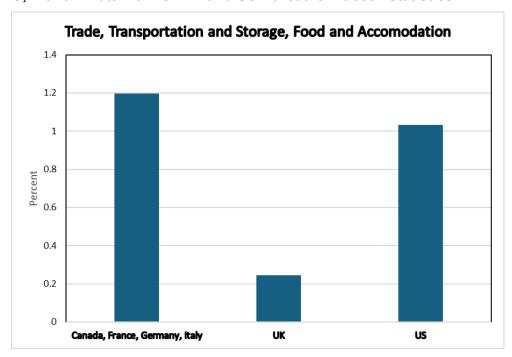


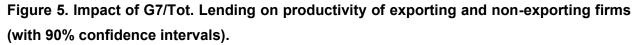
Figure 3. Local projection estimation. Impact of foreign lending on cumulated growth of Multifactor Productivity (with 90% confidence intervals).

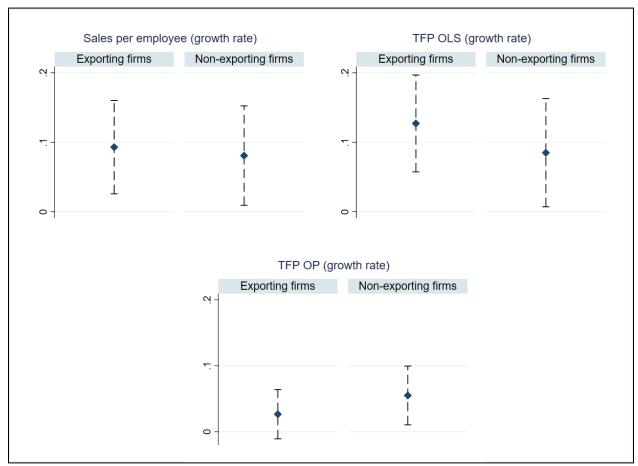


NOTES: The figure reports the evolution of the coefficient β_h from a regression of the following form: $\Delta MFP_{i,t+h} = \alpha_h + \beta_h * International Lending_{i,t-1} + \Phi Controls_{i,t-1} + \theta_i + \partial_t + \varepsilon_{i,t+h}$ for h=0,...,7. $\Delta MFP_{i,t+h}$ is the change in (log) multifactor productivity of country i between t+h and t. Each regression includes country (θ_i) and time (∂_t) fixed effects. The solid blue line reports the coefficients β_h while the grey area reports the 90% confidence intervals for each horizon h with bootstrap standard errors (400 replications). The coefficient β_h gives the cumulative response of country's MFP up to time t+h to a 1% shock in International Lending at time t-1. Φ includes $Regulatory\ Quality$, $Economic\ Complexity$, $R\&D_Expenditure\ (\%GDP)$ and $Human\ Capital\ Index$.

Figure 4. Average (2014-2017) annual growth rate of GDP per hour worked in SIC section G, H and I. Data from OECD and US Bureau of Labour Statistics

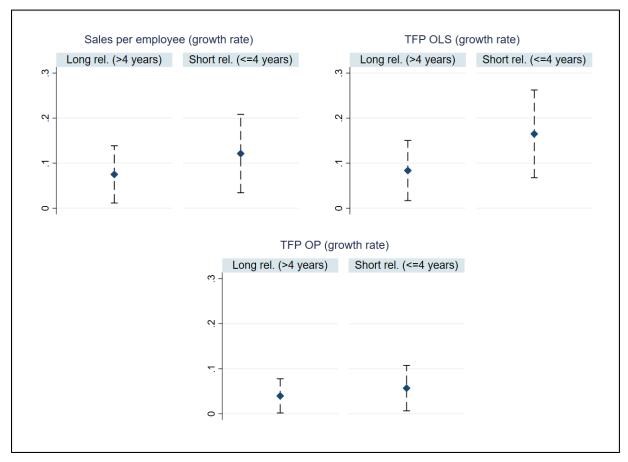






NOTES: The figure reports the marginal effects with 90% confidence intervals of an increase in $G7 \setminus Tot$. Lending of bank b on the sample of exporting and non-exporting firms. Marginal effects derive from the calculation of the interaction term in the following equation: $Y_{f,t} = \alpha + \beta_1 (G7 \setminus Tot$. Lending $b_{t,t} * Exporting_{f,t-1}) + \beta_2 Bank Controls_{b,t} + \beta_3 Firm Controls_{f,t} + \partial_b + \theta_f + \lambda_{j,z,t} + \varepsilon_{i,t}$, where the dependent variable is the firm-level growth rate of alternatively: i) Sales per employee (top left panel), ii) TFP calculated with OLS (top right panel), and iii) TFP calculated with the Olley and Pakes (1996) algorithm (bottom panel), and Exporting is a dummy taking value 1 for firms that at year t-1 report a share of domestic to total turnover different from 100%, and 0 otherwise. Standard errors are clustered at firm level. Firm controls: debt growth rate, lagged tot. assets in log, age, lagged tangible/tot. assets. Bank controls: Capital/assets, ROA.

Figure 6. Impact of G7/Tot. Lending on productivity of firms, short vs long lending relationship (with 90% confidence intervals).



NOTES: The figure reports the marginal effects with 90% confidence intervals of an increase in $G7\Tot.Lending$ of bank b on the sample of firms with a long and short lending relationship with bank b. Marginal effects derive from the calculation of the interaction term in the following equation: $Y_{f,t} = \alpha + \beta_1 \left(G7\Tot.Lending_{b,t} * Long\,rel._{f,t} \right) + \beta_2 Bank\,Controls_{b,t} + \beta_3\,Firm\,Controls_{f,t} + \partial_b + \theta_f + \lambda_{j,z,t} + \varepsilon_{i,t}, \text{ where the dependent variable is the firm-level growth rate of alternatively: } Sales per employee (top left panel), <math>ii$) TFP calculated with OLS (top right panel), and iii) TFP calculated with the Olley and Pakes (1996) algorithm (bottom panel), and $Long\,rel.$ is a dummy taking value 1 if firm f has a lending relationship with bank b that at year t is longer than 4 years, and 0 otherwise. Standard errors are clustered at firm level. Firm controls: lagged domestic/tot. turnover, debt growth rate, lagged tot. assets in log, age, lagged tangible/tot. assets. Bank controls: Capital/assets, ROA.

Appendix A. Summary statistics and additional data

Table A.1. List of countries in the country-level analysis.

List of countries in the sample

Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States of America

Table A.2. Summary statistics of the country-level variables.

Variable	N. Obs.	Mean	SD	Min	Median	Max
GDP per hour worked (growth rate) GDP Manufacturing per hour	325	0.948	1.539	-5.961 -	0.914	9.139
worked (growth rate) Multifactor Productivity (growth	265	2.215	4.170	11.690	2.100	17.540
rate)	319	0.330	1.391	-4.220	0.351	4.414
International Lending (log)	323	13.017	2.016	3.738	13.329	16.354
Regulatory Quality	290	1.388	0.383	0.135	1.450	2.040
Economic Complexity	325	1.367	0.674	-0.588	1.440	2.771
R&D_Expenditure	311	2.152	0.872	0.342	2.156	4.627
Human Capital Index	325	3.270	0.361	2.230	3.330	3.774
Inflows Loans (log)	312	12.587	1.514	8.110	12.571	16.107
Exports (%GDP)	325	0.436	0.277	0.089	0.336	1.394

Table A.3. Summary statistics of the bank-firm dataset.

	N.			_
Variable	Obs.	Mean	SD	Median
<u>Firms</u>				
Sales per employee (growth rate)	44,214	10.331	39.991	4.404
TFP OP (growth rate)	41,411	-0.078	20.590	0.260
TFP OLS (growth rate)	44,150	4.160	38.663	4.845
Domestic/tot. turnover	43,856	0.924	0.190	1.000
Debt (growth rate)	44,214	0.208	0.975	-0.018
Tot. assets (log)	44,214	9.880	1.341	9.635
Age	44,214	30.337	21.956	24.295
Tangible/tot. assets	44,124	0.304	0.264	0.232
<u>Banks</u>				
Capital/tot. assets	44,214	0.118	8.639	0.036
ROA	44,214	0.005	0.005	0.006
G7/Tot. Lending	44,214	13.231	13.089	8.852

Figure A.1. Evolution of average bank internationalisation measures over time.

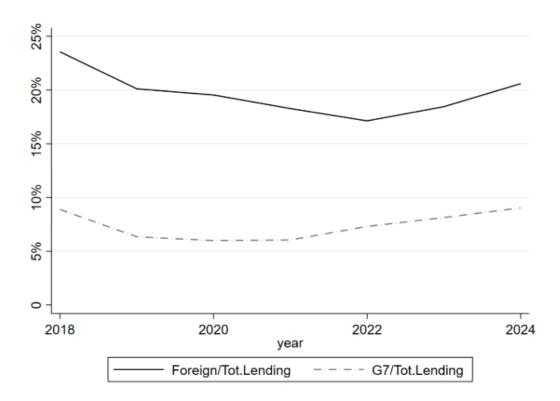
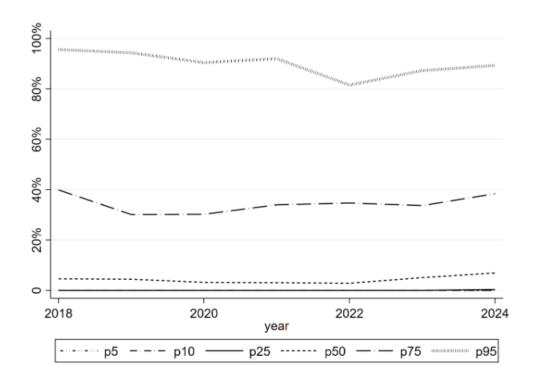


Figure A.2. Evolution of the distribution of Foreign/Tot. Lending over time.



Appendix B. TFP Calculation

We calculate TFP growth at firm level with OLS and following the methodology developed by Olley and Pakes (1996).

First, by linearizing a Cobb-Douglas production function, we estimate the following regressions with OLS:

$$y_{it} = \alpha_0 + \alpha_k * k_{i,t} + \alpha_l * l_{i,t} + \lambda_t + \varepsilon_{i,t}$$
(A.1)

The dependent variable $(y_{i,t})$ is the log of real sales. We convert sales from FAME into real values using a 2-digit NACE domestic output industry deflator (2022 = 100) from the Office of National Statistics (ONS). Capital stock $(k_{i,t})$ is calculated as the log of fixed assets, that is deflated with the industry invariant Gross fixed capital formation deflator (2022 = 100) from the ONS. Labour $(l_{i,t})$ is calculated as the log of the total number of employees. Year fixed effects complete the specification. TFP is calculated as the residual of such OLS regression, while its growth rate as its first difference.

OLS estimation of TFP might provide biased results because of simultaneity between unobserved productivity shocks and inputs k and l in period t. This violates the exogeneity assumption and leads to an upward bias of the input coefficients (see Bournakis and Mallick, 2018; Francis et al., 2020 and Yasar et al, 2008 for a detailed discussion). Moreover, the OLS estimate is affected by selection bias resulting from the relationship between productivity shocks and the probability of exit from the market. When firm profitability is related to its capital stock, then a firm with a larger capital stock has a higher probability of remaining in the market despite a low productivity shock than a firm with a smaller capital stock, since a higher capital stock means higher expected future profits. This negative correlation between capital stock and probability of exit for a given productivity shock causes the coefficient on factor capital to be biased downward (Yasar et al., 2008). Despite these limitations, calculating TFP with OLS remains a widespread technique in the literature because of its easiness of calculation and straightforward interpretation. Also, results from more sophisticated techniques are usually highly correlated with OLS estimates (Van Beveren, 2012). All in all, we decide to estimate TFP in this way and use it as our benchmark, as it often happens in the empirical literature (Van Beveren, 2012).

²⁵ Simultaneity arises because productivity is known to the firm (but not to the econometrician) when they choose their input level. Firms increase their use of inputs as a result of positive productivity shocks. OLS estimation of production functions yields biased parameter estimates because it does not account for the unobserved productivity shocks. A fixed-effect estimator would solve the simultaneity problem only if assuming that the unobserved, firm-specific productivity is time-invariant, an unrealistic assumption.

Then, to obtain a more robust measure of TFP, we follow the algorithm developed by Olley and Pakes (1996), that propose a semi-parametric approach to deal with the main flaws of OLS estimation. Starting from a classical Cobb-Douglas production function, they first set up a profit maximization problem to derive investment as a proxy for unobserved productivity w_{it} (and capital). At the beginning of each period, firms decide whether to exit the market or not, based on their productivity. If the firm decides to remain in the market, it also sets the amount of investment and labour. The investment function depends on two state variables, capital stock and productivity, and implies that future productivity is increasing in the current productivity shock, so firms that experience a large positive productivity shock at time t will invest more at time t+1. Capital stock is accumulated as $k_{i,t-1}=(1-\delta)k_{i,t}+i_{i,t-1}$, where i (investment) is $i_{i,t}=(\omega_{i,t},k_{i,t})$. By defining the inverse of investment as $\omega_{i,t}=(i_{i,t},k_{i,t})$, the production function becomes: $y_{i,t}=a_1*l_{i,t}+\varphi(k_{i,t},i_{i,t})+\varepsilon_{i,t}$, where $\varphi(k_{i,t},i_{i,t})=a_0+a_k*k_{i,t}+h(k_{i,t},i_{i,t})$.

The algorithm proceeds in two steps. In the first step, an OLS is used to estimate the production function and obtain the labour coefficient a_1 (the variable input). The function $\varphi(k_{i,t},i_{i,t})$ is approximated with a higher-order polynomial in $i_{i,t}$ and $k_{i,t}$. In the second step, the OP algorithm runs a regression of $y_{i,t} - \hat{a}_1 * l_{i,t}$ on $\hat{\varphi}(k_{i,t},i_{i,t})$ to estimate a_k (the state input), by assuming that that productivity $\omega_{i,t}$ follows a first-order Markov process. After mathematical manipulation, the equation of the second stage in the OP algorithm becomes:

$$y_{i,t} - \hat{a}_1 * l_{i,t} = a_k * k_{i,t} + f(\hat{\varphi}(k_{i,t-1}, i_{i,t-1}) - a_0 - a_k * k_{i,t-1}) + \theta_{i,t} + \varepsilon_{i,t}.$$

This is a control function without any economic interpretation that is approximated by a higher-order polynomial. However, using a non-linear estimation, it is possible to get an unbiased capital coefficient a_k .

The rationale behind the second step in OP is that the capital stock is predetermined in period t, as the investment (the proxy variable) is decided in period t-1. Hence, in estimating the production function, $k_{i,t}$ is exogenous to $\theta_{i,t}$ (the productivity shock term) and is not affected by productivity. This way, the OP algorithm addresses the simultaneity bias between $\omega_{i,t}$ and $k_{i,t}$ under the assumption that labour is perfectly flexible (non-dynamic).

To perform the OP estimation, we calculate a dummy indicating firm exit by exploiting information from FAME on the company status, i.e. the dummy takes value of 1 when the firm moves from an active to inactive status. The investment is calculated as the first difference of real fixed assets plus real depreciation, where to obtain real values we use the capital asset deflator from the ONS, and then we transform it in log. Materials costs, that we use as an additional free parameter alongside with labour, are the log real cost of sales, where the deflator is the industry

invariant material deflator (ONS), and k and l are defined as before. Year dummies complete the specification in the first stage and standard errors are bootstrapped with 50 replications. TFP and its growth rate are defined as before. Calculations are undertaken with the Stata command by Yasar et al. (2008).

Appendix C. Additional country-level results

Table C.1. Effect of banking sector internationalization on Multifactor Productivity. Quantile regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Yea	arly observa	ations			Collaps	ed (3-years a	verages)	
Dependent: Multifactor Productivity (growth rate)	5th	25th	50th	75th	95th	5th	25th	50th	75th	95th
International Lending (log, lag)	0.2016	0.1892*	0.1789**	0.1683*	0.1508	0.2128#	0.2063**	0.2000***	0.1956***	0.1898*
	(0.1590)	(0.0989)	(0.0752)	(0.0981)	(0.1854)	(0.1317)	(0.0808)	(0.0539)	(0.0662)	(0.1064)
Regulatory Quality (lag)	-0.2950	-0.1902	-0.1035	-0.0139	0.1331	-0.2550	-0.1865	-0.1199	-0.0740	-0.0134
	(1.1930)	(0.7421)	(0.5640)	(0.7362)	(1.3911)	(1.4116)	(0.8657)	(0.5777)	(0.7091)	(1.1408)
Economic Complexity (lag)	0.4935	0.1353	-0.1607	-0.4667	-0.9690	-0.7423	-0.4090	-0.0843	0.1392	0.4343
	(1.7959)	(1.1170)	(0.8491)	(1.1082)	(2.0956)	(2.4513)	(1.5022)	(1.0041)	(1.2299)	(1.9996)
R&D_Expenditure (%GDP, lag)	1.0171	0.9594*	0.9117**	0.8624#	0.7814	1.4737*	1.4110***	1.3499***	1.3079***	1.2524*
	(0.9230)	(0.5741)	(0.4362)	(0.5695)	(1.0760)	(0.8800)	(0.5396)	(0.3601)	(0.4420)	(0.7120)
Human Capital Index	-0.1131	0.5241	1.0507	1.5950	2.4885	0.3637	0.6790	0.9861	1.1976	1.4767
	(4.6162)	(2.8713)	(2.1823)	(2.8486)	(5.3839)	(5.4301)	(3.3296)	(2.2216)	(2.7278)	(4.3892)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	321	321	321	321	321	117	117	117	117	117
Number of countries	20	20	20	20	20	20	20	20	20	20

NOTES: Fixed effects quantile regression. Period 1998-2019. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table C.2. Effect of banking sector internationalization on domestic productivity, controlling for banking system stability.

	(1)	(2)	(3)	(4)	(5)	(6)
	<u>Ye</u>	arly observations		<u>Colla</u>	psed (3-years ave	rages)
VARIABLES	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)
International Lending (log, lag)	0.2011**	0.6950***	0.1664**	0.1980***	0.6304***	0.1768**
	(0.0962)	(0.2577)	(0.0835)	(0.0715)	(0.1961)	(0.0858)
Regulatory Quality (lag)	0.7508	-1.3153	0.1089	1.0545#	0.1306	0.4292
	(0.6158)	(2.1827)	(0.4994)	(0.6514)	(2.2790)	(0.5241)
Economic Complexity (lag)	0.0387	6.0893*	-0.2675	-0.6776	2.8600	-0.0990
	(0.9593)	(3.5229)	(0.8688)	(1.4252)	(3.2339)	(1.0232)
R&D_Expenditure (%GDP, lag)	1.2736**	0.9395	0.8078#	1.9247***	2.5090**	1.3785**
	(0.6149)	(1.6933)	(0.5332)	(0.6846)	(1.2322)	(0.5363)
Human Capital Index	2.2842	-5.1504	3.7992#	0.4796	-2.6329	3.8652
	(2.6910)	(10.4719)	(2.3315)	(3.3392)	(9.2717)	(3.1428)
Inflows Loans (log, lag)	-0.0977	-0.2900	-0.1919	-0.2431	-0.5618	-0.3164*
	(0.1683)	(0.2988)	(0.1763)	(0.2298)	(0.4849)	(0.1744)
Exports (%GDP, lag)	0.2474	-0.2165	1.9945	0.2375	0.2914	2.1170
	(1.9258)	(7.5737)	(1.8605)	(1.9867)	(4.9837)	(1.7424)
Banking sys. Z-score (lag)	0.0077	0.0564	0.0169	0.0107	0.1076#	0.0316#
	(0.0228)	(0.0620)	(0.0214)	(0.0262)	(0.0672)	(0.0214)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	297	241	291	105	85	104
R-squared	0.3332	0.4213	0.4677	0.4011	0.6013	0.5519
Number of countries	20	16	20	20	16	20

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table C.3. Effect of banking sector internationalization on domestic productivity, controlling for financial system size (deposits).

	(1)	(2)	(3)	(4)	(5)	(6)
		early observations	` ,		apsed (3-years aver	
VARIABLES	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)
International Lending (log, lag)	0.2143* (0.1238)	0.8253*** (0.2171)	0.1714* (0.0878)	0.2049** (0.0877)	0.6395*** (0.2287)	0.1835** (0.0769)
Regulatory Quality (lag)	0.5676 (0.7181)	-2.2293 (2.2818)	0.0298 (0.6631)	1.0044 (0.7633)	-0.8608 (2.5836)	0.4997 (0.6481)
Economic Complexity (lag)	-1.0713 [°] (0.9757)	1.5146 (2.9621)	-1.1918 [°] (0.9213)	-1.5530 [°] (1.3614)	-0.4571 [°] (2.7752)	-0.8100 [°] (0.9668)
R&D_Expenditure (%GDP, lag)	1.6154* [*] (0.7771)	2.9214 (2.3689)	1.1564* [′] (0.6721)	2.3506*** (0.6649)	3.2975** (1.5511)	1.7790*** (0.5432)
Human Capital Index	0.5482 (3.8595)	-3.6439 (11.5263)	2.8785 (3.2800)	0.9187 (3.9628)	-7.9523 (12.2401)	3.8472 (3.6530)
Inflows Loans (log, lag)	-0.1586 (0.1681)	-0.4549# (0.2834)	-0.2172 (0.1876)	-0.2199 (0.2047)	-0.4701 (0.4631)	-0.2258 (0.1575)
Exports (%GDP, lag)	-1.8124 (2.4723)	-5.5669 (9.9840)	0.3911 (2.2305)	-0.4222 (2.1749)	-5.8572 (4.9175)	1.5893 (1.9025)
Financial sys. deposits (%GDP, lag)	0.0163 (0.0173)	0.0592 (0.0476)	0.0064 (0.0173)	0.0043 (0.0099)	-0.0071 (0.0321)	-0.0081 (0.0093)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264	209	258	97	77	96
R-squared	0.3417	0.4488	0.4601	0.3961	0.5801	0.5440
Number of countries	20	15	19	20	15	19

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table C.4. Effect of banking sector internationalization on domestic productivity, controlling for banking system size (total assets).

	(1)	(2)	(3)	(4)	(5)	(6)
		Yearly observations			psed (3-years ave	
VARIABLES	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)
International Lending (log, lag)	0.1990* (0.1077)	0.6837*** (0.2253)	0.1718** (0.0842)	0.1790** (0.0724)	0.6567*** (0.2214)	0.1765** (0.0823)
Regulatory Quality (lag)	0.7844 (0.7007)	-2.2276 (2.0810)	0.1085 (0.5728)	1.0422* (0.5814)	0.6713 (2.4597)	0.4387 (0.4765)
Economic Complexity (lag)	-0.3463 (0.9774)	4.7910 (3.5462)	-0.4432 (0.9233)	-0.7892 (1.4721)	2.6360 (3.4792)	-0.1843 (1.1388)
R&D_Expenditure (%GDP, lag)	1.3738**	1.5558 (1.8474)	0.9350# (0.5732)	2.0127***	3.1022** (1.3031)	1.5425***
Human Capital Index	0.0324 (3.5824)	-13.4053 (11.6784)	2.8583 (3.2870)	-0.5047 (3.9466)	-0.8009 (11.2404)	4.1712 (3.3469)
Inflows Loans (log, lag)	-0.1125 (0.1641)	-0.2828 (0.2907)	-0.1989 [°] (0.1725)	-0.2285 [°] (0.2340)	-0.3416 (0.4392)	-0.2554# (0.1738)
Exports (%GDP, lag)	-0.5784 [°] (2.5391)	-0.7589 [°] (8.7487)	1.1398 (2.2684)	0.3817 (1.9213)	-0.0176 (5.9067)	1.8143 (1.9801)
Bank. sys. assets (%GDP, lag)	0.0048 (0.0099)	0.0269 (0.0207)	-0.0006 (0.0072)	0.0041 (0.0068)	-0.0022 [°] (0.0153)	-0.0018 (0.0056)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	282	227	276	103	83	102
R-squared	0.3510	0.4324	0.4717	0.4071	0.5825	0.5416
Number of countries	21	16	20	21	16	20

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.15.

Table C.5. Effect of banking sector internationalization on domestic productivity, controlling for stock market returns.

	(1)	(2)	(3)	(4)	(5)	(6)
	<u>Ye</u>	early observations		Colla	apsed (3-years ave	
	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)	GDP per hour worked (growth rate)	GDP Manufacturing per hour worked (growth rate)	Multifactor Productivity (growth rate)
VARIABLES						
International Lending (log, lag)	0.2013**	0.6924***	0.1673**	0.1989***	0.6768***	0.1863**
	(0.0876)	(0.2407)	(0.0772)	(0.0692)	(0.1968)	(0.0830)
Regulatory Quality (lag)	0.7560	-2.1655	0.1125	1.0656*	0.8131	0.4695
	(0.6614)	(2.1312)	(0.5197)	(0.6264)	(2.4517)	(0.4801)
Economic Complexity (lag)	-0.1469	5.4450#	-0.4245	-0.7207	2.7364	-0.1095
	(0.9560)	(3.5553)	(0.9113)	(1.3817)	(3.3484)	(1.0746)
R&D_Expenditure (%GDP, lag)	1.3136**	1.1509	0.8618*	1.9682***	3.0373***	1.4752***
	(0.5543)	(1.6358)	(0.4574)	(0.6155)	(1.1389)	(0.5022)
Human Capital Index	2.2618	-8.3275	3.6130	0.4047	-3.4111	2.4431
	(2.9700)	(9.9853)	(2.7650)	(3.3079)	(9.0652)	(2.9212)
Inflows Loans (log, lag)	-0.0189	-0.2096	-0.1065	-0.2232	-0.3981	-0.2868*
	(0.1229)	(0.2602)	(0.1442)	(0.2169)	(0.4065)	(0.1683)
Exports (%GDP, lag)	-0.1896	-1.8882	1.5513	0.1156	0.0544	1.6478
	(2.0404)	(7.8824)	(1.9259)	(1.9984)	(5.4459)	(1.8738)
Stock Market Return. (lag)	0.0174	0.0099	0.0173*	0.0013	-0.0270	-0.0100
	(0.0142)	(0.0340)	(0.0096)	(0.0147)	(0.0199)	(0.0095)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	301	245	295	105	85	104
R-squared	0.3458	0.4136	0.4772	0.4000	0.5890	0.5464
Number of countries	21	16	20	21	16	20

NOTES: Period 1998-2019. Bootstrap standard errors (400 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D. Additional country-sector level results

Table D.1. Effect of banking sector internationalization on zombie firms. The dependent variable is the sector-country average of a dummy that takes value 1 for firms reporting interest payments exceeding operational profit for three consecutive years and not considered to be high labour growth firms.

	(1)	(2)	(3)	(4)	(5)	(6)
	<u>Yea</u>	rly observa	tions_	Collapse	ed (3-years	averages)
VARIABLES			Zomb	ie firms		
International Lending (log, lag)	-0.011***	-0.011***	-0.011*	-0.007*	-0.007*	-0.010*
	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)
Regulatory Quality (lag)	0.020**	0.020**	0.012	0.030***	0.031**	-0.000
	(800.0)	(800.0)	(0.013)	(0.011)	(0.012)	(0.014)
Economic Complexity (lag)	0.011	0.009	0.003	0.016	0.017	0.104**
	(0.013)	(0.013)	(0.030)	(0.014)	(0.015)	(0.051)
R&D_Expenditure (%GDP, lag)	0.000	0.001	0.005	-0.002	-0.002	-0.033**
	(800.0)	(800.0)	(0.010)	(0.009)	(0.010)	(0.015)
Human Capital Index	-0.043**	-0.047**	0.069	-0.058***	-0.055**	0.153
	(0.020)	(0.022)	(0.160)	(0.019)	(0.022)	(0.161)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Time FE	No	Yes	Yes	No	Yes	Yes
Country*Sector FE	No	No	Yes	No	No	Yes
Additional sector-countries controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	630	605	605	233	225	225
R-squared	0.289	0.378	0.649	0.365	0.433	0.826
Number of countries	6	6	6	6	6	6
Number of sector-countries	51	51	51	51	51	51

NOTES: Period 2003-2019. Additional sector-country controls are a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown, equity over debt, nominal intangible fixed assets over nominal capital. All sector-country controls are sector-country specific weighted averages. Standard errors clustered at sector-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2. Effect of banking sector internationalization on total investment.

	(1)	(2)	(3)	(4)	(5)	(6)
	<u>Ye</u>	early observa	ations	Collaps	sed (3-years	averages)
VARIABLES			Total Inve	estment (log)		
International Lending (log, lag)	0.204**	0.206**	-0.027	0.309***	0.309***	0.052
	(0.090)	(0.094)	(0.033)	(0.108)	(0.113)	(0.078)
Regulatory Quality (lag)	-0.239	-0.243	0.140	-0.658*	-0.673*	-0.203
	(0.300)	(0.314)	(0.157)	(0.335)	(0.339)	(0.224)
Economic Complexity (lag)	-0.056	-0.048	0.217	-0.466	-0.467	0.142
	(0.279)	(0.294)	(0.275)	(0.327)	(0.337)	(0.268)
R&D_Expenditure (%GDP, lag)	0.286*	0.288*	-0.087	0.507***	0.516***	-0.074
	(0.148)	(0.156)	(0.087)	(0.177)	(0.185)	(0.130)
Human Capital Index	0.452	0.458	-2.879**	1.055**	1.080**	-2.421
	(0.415)	(0.433)	(1.172)	(0.427)	(0.433)	(1.480)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Time FE	No	Yes	Yes	No	Yes	Yes
Country*Sector FE	No	No	Yes	No	No	Yes
Additional sector- countries controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	957	957	334	325	325
R-squared	0.606	0.629	0.921	0.643	0.662	0.961
Number of countries	8	8	8	8	8	8
Number of sector- countries	70	70	70	70	70	70

NOTES: Period 1998-2019. Additional sector-country controls are a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. Standard errors clustered at sector-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1,

Table D.3. Effect of banking sector internationalization on intangible investment

	(1)	(2)	(3)	(4)	(5)	(6)
	Yea	arly observa	tions	<u>Collaps</u>	ed (3-years a	averages)
VARIABLES		1	Intangible Ir	nvestment (lo	og)	
International Lending (log, lag)	0.344**	0.306**	-0.086	0.562***	0.561***	-0.330
	(0.134)	(0.129)	(0.196)	(0.160)	(0.181)	(0.471)
Regulatory Quality (lag)	0.011	0.078	-0.260	-0.154	-0.373	-1.044
	(0.560)	(0.638)	(0.898)	(0.531)	(0.590)	(1.146)
Economic Complexity (lag)	-1.258**	-1.104**	1.060	-1.722***	-1.938***	0.939
	(0.507)	(0.525)	(1.556)	(0.545)	(0.582)	(2.804)
R&D_Expenditure (%GDP, lag)	0.273	0.400	1.276*	0.236	0.417	0.603
	(0.327)	(0.364)	(0.668)	(0.314)	(0.319)	(0.912)
Human Capital Index	1.479	1.063	0.665	2.741***	2.816**	4.721
	(1.006)	(1.112)	(7.788)	(1.007)	(1.110)	(10.134)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Time FE	No	Yes	Yes	No	Yes	Yes
Country*Sector FE	No	No	Yes	No	No	Yes
Additional sector-	V	V	V	V	V	V
countries controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	336	289	277	190	188	174
R-squared	0.497	0.591	0.852	0.547	0.608	0.854
Number of countries	8	8	8	8	8	8
Number of sector- countries	58	58	58	58	58	58

NOTES: Period 1998-2019. Additional sector-country controls are a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. Standard errors clustered at sector-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.4. Effect of bank international lending on country-sector level productivity. System-GMM on collapsed sample. All variables are treated as endogenous. Dependent: Real revenue per employee (growth rate).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Real revenue per employee	-0.059	-0.054	-0.061	-0.055	-0.065	-0.065
(growth rate, lag)	-0.039	-0.034	-0.001	-0.033	-0.003	-0.003
	(0.093)	(0.093)	(0.091)	(0.094)	(0.089)	(0.090)
International Lending (log, lag)	1.300*	1.329*	1.334*	1.439**	1.409**	1.424*
	(0.655)	(0.667)	(0.682)	(0.718)	(0.700)	(0.723)
Regulatory Quality (lag)	-3.685	-3.759*	-3.697	-3.775*	-3.650	-3.681
	(2.267)	(2.239)	(2.224)	(2.251)	(2.260)	(2.264)
Economic Complexity (lag)	-6.601***	-6.499***	-6.417***	-6.441***	-6.303***	-6.213***
	(1.465)	(1.416)	(1.411)	(1.431)	(1.457)	(1.493)
R&D_Expenditure (%GDP, lag)	4.730***	4.746***	4.705***	4.798***	4.694***	4.715***
	(1.095)	(1.077)	(1.081)	(1.086)	(1.118)	(1.113)
Human Capital Index	6.023**	6.137**	6.220**	6.191**	6.295**	6.178**
	(2.494)	(2.489)	(2.513)	(2.498)	(2.556)	(2.604)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country*Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional sector-countries controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	325	325	325	325	325	325
Prob>AR(2)	0.234	0.267	0.276	0.276	0.288	0.253
Prob>Hansen	0.999	0.856	0.727	0.718	0.209	0.217
N. of instruments	110	90	84	85	74	69
Number of sector-countries	70	70	70	70	70	70

NOTES: Period 1998-2019. Additional sector-country controls are real investment, a dummy for mature and high growth firms, firm's market share based on nominal revenues, capital cost over intermediate inputs, capital markdown. All variables are treated as endogenous. Column 1: all available lags of each variable are used as instruments. Column 2: all available lags of the country-level variables are used as instruments, only the most three recent lags of the sector-country level variables are used as instruments. Column 3: only the most three recent lags of each variable are used as instruments. Column 4: all available lags of the country-level variables are used as instruments, only the most two recent lags of the sector-country level variables are used as instruments. Column 5: only the most two recent lags of each variable are used as instruments. Column 6: only the most two recent lags of country-level variables are used as instruments, only the most recent lag of sector-country level variables is used as instruments. Prob>AR(2) reports the p-value of a AR test for second order autocorrelated disturbances in the first differenced equations. Prob>Hansen reports the p-value of a Hansen test where the null hypothesis is instrument validity. Standard errors in parentheses are clustered at country level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix E. Additional firm-level results

Table E.1. Effect of bank lending to foreign G7 economies on different measures of firms' productivity. Alternative fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales per	employee (gr	owth rate)	<u>TFF</u>	OLS (growt	<u>h rate)</u>	<u>TFP</u>	OP (growth	rate)
VARIABLES									
G7/Tot.Lending	0.0416**	0.0951**	0.0973**	0.0367*	0.0872**	0.1054***	0.0206**	0.0266	0.0421*
	(0.0188)	(0.0404)	(0.0390)	(0.0203)	(0.0417)	(0.0405)	(0.0103)	(0.0236)	(0.0231)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	No	No	Yes	No	No	Yes	No
ZIP*Industry FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Bank*ZIP FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	44,167	44,166	44,171	44,088	44,087	44,092	41,292	41,291	41,291
R-squared	0.3086	0.3355	0.3657	0.2553	0.2621	0.2977	0.3050	0.3088	0.3694

Table E.2. Effect of bank lending to foreign G7 economies on different measures of firms' productivity. Controlling for bank size.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales per	employee (gr	owth rate)	TFP OLS (growth rate)			TFP OP (growth rate)		
VARIABLES									
G7/Tot.Lending	0.0440**	0.1908***	0.1629**	0.0431**	0.1943***	0.1312*	0.0185*	0.0733**	0.0210
	(0.0188)	(0.0618)	(0.0710)	(0.0205)	(0.0657)	(0.0742)	(0.0106)	(0.0374)	(0.0451)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry*Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
ZIP*Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry*ZIP*Time FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	44,214	44,213	38,385	44,135	44,134	38,316	41,335	41,334	35,638
R-squared	0.3846	0.3848	0.5705	0.3171	0.3174	0.5205	0.3845	0.3849	0.5618

Table E.3. Effect of bank foreign lending on different measures of firms' productivity. System GMM estimation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Sales	per emplo	yee (growt	h rate)		TFP OLS (g	rowth rate)		TFP OP (g	rowth rate)	
Lagged dependent	-0.110***	-0.112***	-0.110***	-0.111***	-0.159***	-0.160***	-0.159***	-0.160***	-0.182***	-0.183***	-0.182***	-0.182***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)	(0.021)
G7/Tot.Lending	0.271**	0.299***			0.190**	0.187***			0.128***	0.105***		
	(0.106)	(0.093)			(0.082)	(0.070)			(0.045)	(0.040)		
Foreign/Tot.Lending			0.117*	0.229***			0.038	0.105			0.036	0.058
			(0.070)	(0.068)			(0.073)	(0.068)			(0.039)	(0.039)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,255	33,255	33,255	33,255	40,561	40,561	40,561	40,561	37,851	37,851	37,851	37,851
Prob>AR(2)	0.00245	0.00356	0.00234	0.00286	0.578	0.669	0.581	0.669	0.451	0.453	0.449	0.449
Prob>Hansen	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001
N. of instruments	19	14	19	14	20	15	20	15	20	15	20	15
Number of firms	13,985	13,985	13,985	13,985	15,198	15,198	15,198	15,198	14,176	14,176	14,176	14,176

NOTES: Period 2018-2024. Columns 1, 3, 5, 7, 9 and 11: all variables treated as endogenous, the instruments matrix is collapsed, only the most recent lag of each variable is used as instrument. Columns 2, 4, 6, 8, 10 and 12: the lagged value of the dependent variable and the main regressor is treated as endogenous, all the other variables as exogenous, the instruments matrix is collapsed, only the most recent lag of each variable is used as instrument. Prob>AR(2) reports the p-value of a AR test for second order autocorrelated disturbances in the first differenced equations. Prob>Hansen reports the p-value of a Hansen J-test where the null hypothesis is instrument validity. Firm controls: lagged domestic/tot. turnover, debt growth rate, lagged tot. assets log, age, lagged tangible/tot.assets. Standard errors in parentheses are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.4. Effect of bank foreign lending on different measures of firms' productivity. System GMM estimation with dependent variables in level.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Sales per er	TFP (OLS (log)	TFP	OP (log)	
Lagged dependent	0.631***	0.631***	0.427***	0.427***	0.402***	0.403***
	(0.068)	(0.068)	(0.039)	(0.039)	(0.048)	(0.048)
G7/Tot.Lending	0.906*		0.002*		0.001**	
	(0.542)		(0.001)		(0.000)	
Foreign/Tot.Lending		0.932*		0.002*		0.001*
		(0.553)		(0.001)		(0.000)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,511	44,511	44,423	44,423	41,648	41,648
Prob>AR(2)	0.250	0.252	0.112	0.107	0.134	0.133
Prob>Hansen	0.136	0.125	0.997	0.983	0.0469	0.0542
N. of instruments	15	15	15	15	15	15
Number of firms	16,759	16,759	16,724	16,724	15,675	15,675

NOTES: Period 2018-2024. The lagged value of the dependent variable and the main regressor is treated as endogenous, all the other variables as exogenous. The instruments matrix is collapsed. Only the most recent lag of each variable is used as instrument. Prob>AR(2) reports the p-value of a AR test for second order autocorrelated disturbances in the first differenced equations. Prob>Hansen reports the p-value of a Hansen J-test where the null hypothesis is instrument validity. Firm controls: lagged domestic/tot. turnover, debt growth rate, lagged tot. assets log, age, lagged tangible/tot.assets. Standard errors in parentheses are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.