Small and Vulnerable: SME Productivity in the Great Productivity Slowdown*

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Abstract

We show that the TFP growth of European micro, small, and medium-sized firms (SMEs) diverged from large firms after the global financial crisis. The average postcrisis TFP growth of medium-sized, small, and micro firms was, respectively, 1.1, 2.9, and 5.4 percentage points lower than that of large firms. This SME productivity gap is larger for firms with more severe credit supply shocks. The gap is partially attributable to a larger postcrisis reduction in intangible capital at SMEs than at large firms. Horseraces suggest that SME indicators are more robust and more powerful predictors of postcrisis TFP growth than other indicators.

Keywords: credit constraint, global financial crisis, productivity, intangible capital, SME
JEL: E22, G32, L11, O30, O47

1. Introduction

Do financial crises hinder the total factor productivity (TFP) growth of micro, small, and medium-sized firms (SMEs) more so than those experienced in large firms? The answer is a resounding yes, based on our evidence from close to three quarters of a million SMEs in Europe after the global financial crisis (GFC; Figure 1). We hereafter call this difference the *SME productivity gap*. Understanding this gap is crucial for deciphering Europe's postcrisis slowdown in productivity, given the predominance of SMEs in the economy; it is also crucial for supporting business dynamics in an inclusive economy because a slow growing SME sector may lead to increasing market concentration (IMF, 2021). Although prior studies have shown how cyclical shocks affect firm growth, no study has directly analyzed the link between the GFC and the resultant SME productivity gap.

This paper aims to quantify and understand this gap. We build a comprehensive cross-country firm-level dataset, merging the Orbis, AMADEUS, and Fitch Connect (formerly Bankscope) datasets. The sample includes over 700,000 firms in 18 European countries. Its coverage of SMEs—according to the European Union's (EU) definition discussed below—is extensive: 53 percent of the sample comprises

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micro firms; 34 percent, small firms; and 10 percent, medium-sized firms. The dataset contains detailed information on firm-level input, output, and balance sheet characteristics, as well as each firm's main banks and bank balance sheet characteristics. For a subset of firms, we also obtain information on their annual patent applications from the Worldwide Patent Statistical Database (PATSTAT).

In Section 2, we document systemic and robust evidence of the SME productivity gap for various sample cuts. The gap is progressively wider for medium, small, and micro firms relative to large firms. It holds when estimated within narrowly defined industry-country groups; therefore, it reflects a firm-level vulnerability to the crisis that is unrelated to industry-country shocks.

The gap does not simply reflect other firm-level characteristics. Running horseraces between SME indicators (i.e., dummy variables for micro, small, and medium-sized firms) and an extensive set of covariates including the precrisis level of TFP, firm age, and balance sheet characteristics—leverage, debt maturity, cash flow, liquidity, and profitability—we find that SME indicators are more robust and powerful predictors of postcrisis TFP growth than other indicators, in particular balance sheet indicators. This finding has significant policy implications because it suggests that policies targeted to SMEs may be more effective in alleviating their growth obstacles than nontargeted policies.

In Section 3, we turn to testing plausible explanations for this gap. The large and abrupt SME productivity gap suggests an intuitive approach in search of an explanation. The gap is likely attributable to large, abrupt shocks instead of a slow-moving force, and to shocks that affect SMEs and large firms differently. The vulnerability of SMEs to the tightening of credit market conditions is a likely candidate in both regards. Credit multiplier models predict that tighter credit constraints during a crisis limit firms' ability to borrow (e.g., Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999). The credit constraints may be tighter for SMEs because they tend to be informationally opaque and dependent on bank financing (Gertler and Hubbard, 1988; Custódio, Ferreira and Laureano, 2013). SMEs are also more likely to rely on local relationship banks (Stein, 2002; Beck et al., 2018), have fewer banking relationships, and face higher obstacles to establish new ones (Rajan, 1992).

We use several complementary approaches to test this credit market explanation. First, we show that SMEs facing more severe tightening of credit conditions experienced a larger TFP growth decline. We use a difference-in-differences (DID) framework and exploit variations in the magnitude of the credit supply shock following the collapse of Lehman Brothers in 2008. The shock was arguably unforeseen from the vantage point of firms and plausibly exogenous to precrisis firm size. Following Duval, Hong and Timmer (2020), we measure the tightening of credit conditions by the average CDS spread of banks in the firm's home country around the time of the collapse of Lehman Brothers on September 15, 2008, or by the average CDS spread of the firm's main creditor banks during the same period. The result is also robust to using alternative measures of credit supply tightening based on bank lending surveys.

Second, we investigate the credit market vulnerability of SMEs through a creditor strength channel. We use two alternative measures of creditor strength. The first is bank capitalization. When credit conditions tighten, banks experience a deterioration in their asset quality. Less capitalized banks face higher pressure to deleverage and cut more lending via the traditional bank lending channel. The second is the bank's presence in the CDS market, the use of which is motivated by extant evidence that CDS trading is associated with sounder fundamentals, higher financing capacity, and lower borrowing cost.[3]

[3]CDS trading can increase the financing capacity of the reference entity because it mitigates problems of limited commitment and asymmetric information. In the former it reduces strategic default by enhancing creditors' bargaining power in ex post renegotiations (Bolton and Oehmke, 2011). In the latter it mitigates the proverbial "lemon problem" by reducing asymmetric information on creditworthy borrowers. For a review of the theoretical and empirical literature, see Augustin

We find that the SME productivity gap was larger when the creditor bank is less capitalized or without a CDS presence.

Third, we provide evidence supportive of the credit market vulnerability of SMEs through a relationship lending channel. Relationship lending is a lending practice based on repeated interactions with borrowers to obtain proprietary borrower information. It has long been recognized as a valuable tool for banks to lend to SMEs that are informationally opaque (Agarwal and Hauswald, 2010; Rajan, 1992). Theory suggests that proprietary borrower information allows relationship banks to adapt their lending during a crisis, mitigating the adverse credit shock to the borrowers. Consistent with this prediction, we find that the SME productivity gap is larger in places where relationship banks have less a presence.

These findings consistently point to the credit market vulnerability of SMEs as a driver of their productivity gap. In our next set of tests, we ask whether the gap can also be attributable to alternative explanations. Drawing on extensive literature on drivers and impediments to productivity growth, we test a number of such explanations. Specifically, we rule out that the SME indicators are simply proxies for firm-level measures of technological leadership and market power. Our results are robust to these controls. Neither do we find evidence that the gap can be explained by management quality, market concentration, resource misallocation, and productivity bottlenecks. We find little evidence that the SME productivity gap varies systematically along these dimensions.

In Section 4, we report a number of extensions and robustness tests. In our extended set of analyses, we investigate the extent to which the SME productivity gap reflects the gap in the intangible investment of SMEs and large firms. We first show that SMEs reduced intangible investment more than large firms after the crisis, consistent with the notion that the SME productivity reflects a slower accumulation of intangible capital in SMEs vis-à-vis large firms. We then quantify the role of intangible capital by drawing inference from two TFP growth measures: a Solow (1957) measure that reflects output growth not explained by physical capital and labor growth and an intangible-augmented measure that reflects output growth not explained by physical capital, intangible capital, and labor growth. We show that intangible capital explains 21 percent of the SME productivity gap under the Solow measure. Finally, we report a battery of robustness tests. We examine alternative measures of credit market conditions, different subperiods, and different subsets of the country sample. We also test implications from potential sample attrition as well as firm entry and exit.

We make several contributions to the literature. To the best of our knowledge, this paper is the first to quantify and explain the TFP growth gap between SMEs and large firms after the GFC. Although a number of researchers have examined the differential impact of business cycles on firms of varying sizes, most have focused on output, employment, and capital. For example, Gertler and Gilchrist (1994) show that smaller firms account for a disproportionate share of the decline in sales and inventory during downturns. Chari, Christiano and Kehoe (2013) extend the sample and show that the responses of large and small firms are roughly the same. Moscarini and Postel-Vinay (2012) show that firms with no more than 50 employees destroy proportionally less employment when aggregate unemployment is high. On the other hand, Chodorow-Reich (2013) and Siemer (2019) show that smaller firms reduced employment more than large firms after the GFC. Using sectoral-level output and employment data on manufacturing, OECD (2017) also shows that the average output per worker of SMEs lagged behind that of large firms after the GFC.

How to reconcile these conflicting findings is an open question. A possible explanation may be

et al. (2014).

the difference in sample and the nature of the shocks. None of these studies can inform TFP because by definition TFP measures output not explained by capital and labor inputs. Direct evidence on firm-level TFP is scant. One notable exception is Krishnan, Nandy and Puri (2015), who show a positive effect of increased credit access on TFP during the period of interstate banking deregulations in the US. Our paper differs from theirs in examining the effect of tight credit conditions during the GFC and explaining the TFP growth gap between SMEs and large firms. Another exception is Duval, Hong and Timmer (2020), who show that firms with higher rollover risk had a larger decline in postcrisis TFP growth. Our results complement their findings in identifying SME indicators as additional TFP growth predictors and in quantifying the role of intangible capital.[4]

Second, our study is based on a comprehensive cross-country dataset with extensive coverage of SMEs, allowing us to consider aggregate implications of our estimates. We thus overcome the limitations of existing papers focusing on a subsample of firms (based on a subset of industries or firm size) or using credit registry data from a single country. The results of these latter papers tend to be unrepresentative of SMEs because they are inferred from firms with borrowing relationships with multiple banks (Khwaja and Mian, 2008; Chodorow-Reich, 2013) and rely on restrictive assumptions about firm-bank relationships.[5]

Third, to our knowledge, this paper is also the first to quantify the role of intangible capital in SME productivity using firm-level data. The role of intangible capital in TFP growth has been explored in aggregate data following the seminal work of Corrado, Hulten and Sichel (2005). Papers with firm-level data typically resort to information on publicly listed firms or on firms seeking specific types of funding. Their focus is typically on the determinants of R&D or other types of intangible investment instead of quantifying the role of intangible capital in firm-level TFP growth (Aghion et al., 2012). Furthermore, public firms are typically large and their capital and production structures are different from those of SMEs. Firms seeking specific types of funding may not be representative of the broad samples of SMEs.

2. Quantifying the SME productivity gap

2.1. Data and measurement

Our firm-level data source is the Orbis historical database from Bureau van Dijk.[6] Orbis is the largest cross-country firm-level database with rich information on financial accounts and productive activities (e.g., output, capital, and employment) for both public and private firms. The data are collected from various sources, including national company registries, and harmonized into an internationally comparable format.

Our final sample includes 18 countries: Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Poland, Portugal, Slovenia, Slovak Republic,

[4]A separate line of literature covers the financing constraints of small firms. Dinlersoz et al. (2018) combine public data on listed firms with census data on private firms and show that small private firms are less leveraged than large private firms and public firms, implying that their credit market access is most limited. Using a cross-country firm-level survey, Beck et al. (2005) show that the growth of small firms is more constrained than that of large firms because of financial constraints; however, this literature does not link firm-level financial constraint to productivity.

[5]See Amiti and Weinstein (2018) for a discussion on identification assumptions.

[6]See Gal, 2013 and Kalemli-Özcan et al., 2015 for details on constructing Orbis historical data.

Spain, Sweden, and the United Kingdom.[7] We follow the how-to guide in Kalemli-Özcan et al. (2015) for constructing a nationally representative sample from the Orbis database.[8]

We follow Gal (2013) and Andrews, Criscuolo and Gal (2016) to clean the firm-level data. The following procedure ensures the consistency and comparability of variables across countries and over time. All nominal variables recorded in U.S. dollars in the original dataset are converted to local currency. They are then deflated using local currency deflators from the OECD Structural Analysis Database (STAN) and converted to 2005 U.S. dollars using the country–industry purchasing power parity exchange rate from Inklaar, O'Mahony and Timmer (2005). We drop financial firms and government-owned firms. We only keep firms that continuously exist during our sample period (4 years before and after the GFC). This sample restriction ensures that pre- and postcrisis TFP growth is measured in the same time period for all firms, thus avoiding contamination of our results with firm entry and exit. In Section 4.2.6, we discuss an extension of our analysis when we relax this sample restriction.

We classify SMEs according to the EU definition. In this definition we take into account three criteria: employee counts, annual turnover, and annual balance sheet total. Micro firms are defined as firms with fewer than 10 employees and whose annual turnover or annual balance sheet total does not exceed EUR 2 million. Small firms are defined as firms with fewer than 50 employees and whose annual turnover or annual balance sheet total does not exceed EUR 10 million. Medium-sized firms are defined as those with fewer than 250 employees and either an annual turnover that does not exceed EUR 50 million or an annual balance sheet not exceeding EUR 43 million. Following this definition, 53 percent of our final sample comprises micro firms; 34 percent, small firms; and 10 percent, medium-sized firms.[9]

We obtain information on firm-bank relationship from the AMADEUS dataset. The BANKER variable in AMADEUS lists up to five of the most important creditor banks for each firm.[10] This information has been used by Giannetti and Ongena (2012), Kalemli-Özcan et al. (2018), Barbiero et al. (2018), and Duval, Hong and Timmer (2020) to study the firm-bank relationship. As in these earlier studies, we use this variable from one vintage of the data (2015), relying on the assumption that firm-bank relationships are sticky and do not significantly change over short periods of time (Giannetti and Ongena, 2012, Kalemli-Özcan et al., 2018).

For firms in the database, we name match creditor banks in AMADEUS with banks in Fitch Connect (formerly Bankscope). No standardized procedure exists to match banks in AMADEUS and Fitch Connect. We use a probabilistic record linkage algorithm to match the bank names from the two

[7]This is the most extensive country sample with available data to calculate firm-level TFP. We are also able to calculate firm-level TFP for the following countries but with less than 100 firms in each of these countries: Austria, Switzerland, Ireland, Hungary, and Luxembourg. Adding them to our final sample does not change our main results.

[8]The coverage of our subsample of manufacturing firms is comparable to Kalemli-Özcan et al. (2015). See, for example, Table D.1.3 in Kalemli-Özcan et al. (2015).

[9]Under the EU SME definition, meeting the employee threshold is mandatory to be considered an SME. But firms may choose to meet either the turnover or the balance sheet total ceiling so that those engage in different economic activities are treated fairly. Using employment as a key criterion to classify firms is theoretically grounded (see, e.g., Burdett and Mortensen, 1998 and Moscarini and Postel-Vinay, 2013). Most extant theories on firm productivity predict a high correlation between output, employment, and other inputs.

[10]The original source of the information is Kompass, which provides directories for companies in more than 70 countries. Kompass collects data from firm registries, Chambers of Commerce, and phone interviews with firm representatives. Firms can also voluntarily register with the Kompass directory.

datasets.[11]

2.2. Measuring productivity

We estimate firm-level productivity using a one-step efficient generalized method of moments procedure by Wooldridge (2009). This procedure builds on the traditional control function approach, which addresses the key challenge in production function estimation: potential simultaneity bias stemming from the fact that firms can make their input choices while knowing their own productivity, but the econometrician cannot observe this productivity.[12] Specifically, we estimate the following production function, using all firms in each (2-digit) industry $\times$ country group:

$$y_{ijct} = a_{ijct} + \beta_{kj} \times k_{ijct} + \beta_{lj} \times l_{ijct-1} + \varepsilon_{ijct} \tag{1}$$

where i, j, c, and t index firm, industry, country, and time, respectively. y, k, and l are the natural logarithms of value-added output, physical capital, and the number of employees, respectively. Finally, a is TFP (in natural logarithm). Output and physical capital stock are expressed in real terms using country–industry level price deflators.[13] The industry-level elasticities β_{kj} and β_{lj} are estimated using the Wooldridge (2009) procedure. Using estimation results from equation 1, firm-level TFP is calculated as

$$a_{ijct} = y_{ijct} - \hat{\beta}_{ks} \times k_{ijct} - \hat{\beta}_{ls} \times l_{ijct-1}$$

where $\hat{\beta}_{ks}$ and $\hat{\beta}_{ls}$ are the estimated coefficients. TFP growth at time t is calculated as $a_{ijct} - a_{ijct-1}$ (i.e., log difference in TFP).

Figure 1 shows the path of TFP growth for SMEs and large firms in our sample. Before the crisis, TFP growth for SMEs was as strong as that for large firms. After the crisis, their trajectories diverged. The TFP of SMEs experienced a large and persistent drop relative to large firms.[14] Table 1 reports the summary statistics.

2.3. Estimating the SME productivity gap

We estimate the SME productivity gap using a Difference in Differences (DID) model:

$$\Delta TFP^{gr}_{ijc} = \alpha_{jc} + \beta_1 Micro_i + \beta_2 Small_i + \beta_3 Medium_i + \gamma X_i + \varepsilon_{ijc} \tag{2}$$

where i, j, and c index firm, industry, and country, respectively. ΔTFP^{gr}_{ijc} is the difference in average TFP growth between the pre- (2004–2007) and postcrisis (2008–2011) periods. The advantage of comparing the average pre- and postcrisis TFP growth is that it allows for a sluggish TFP response.

[11] The matching is implemented by Stata's *reclink2* package. Kalemli-Özcan, Laeven and Moreno (2018) similarly use name matching to merge Kompass and Bankscope databases.

[12] Compared to previous two-step approaches (e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003), the Wooldridge (2009) approach addresses the problem in identifying the variable input (e.g., labor) coefficient as shown in Ackerberg, Caves and Frazer (2015). Robust standard errors are also easier to obtain with the one-step approach compared to previous approaches.

[13] Country–industry level price deflators have also been used in Gopinath et al. (2017) and Duval, Hong and Timmer (2020) among others because firm-level prices are not observed. As a result, our TFP measure does not reflect sector price variations.

[14] The magnitude of TFP growth in our sample is comparable to aggregate statistics. For example, according to EU KLEMS, the average annual TFP growth was 0.5, 0.3, and -0.4 percent in 2002-2007 for EU-12 countries, France, and Spain, respectively. It was -1, -0.9, and -0.4 percent in 2008-2011 for EU-12 countries, France, and Spain, respectively.

A similar approach has been used to study the role of balance sheet vulnerabilities in employment (Chodorow-Reich, 2013) and TFP growth (Duval, Hong and Timmer, 2020) as well as the role of household wealth in employment (Mian and Sufi, 2014).

Our main variable of interest is a set of dummy variables for micro, small, and medium-sized firms (hereafter SME indicators). The coefficients for the SME indicators β_1, β_2, and β_3 captures the postcrisis TFP growth gap between micro, small, and medium-sized firms, relative to large firms. If SMEs experienced a larger drop in postcrisis TFP growth relative to the precrisis growth vis-à-vis large firms, we expect the coefficients for the SME indicators to be negative.

We include fixed effects at the four-digit industry $\times$ country level. These fixed effects are important because the literature has established systemic differences across industries in financial dependence (Rajan and Zingales, 1998) and exposure to shocks in trade (Alcalá and Ciccone, 2004) that may potentially affect productivity. By including industry-country fixed effects, we are able to rule out such channels. We cluster standard errors at the industry $\times$ country level. In extended specifications, we also include a vector of firm-level characteristics X_i to be specified below.

Our identification assumption is that, conditional on these controls, any remaining variation associated with the post-GFC TFP does not vary systematically with precrisis SME status. In other words, the supply or demand conditions of SMEs did not decline more than those of large firms within the same industry and country. Similar assumptions on industry-country level conditions have been used in Duval, Hong and Timmer (2020) and Kalemli-Özcan, Laeven and Moreno (2018). We think this is a reasonable assumption because firms likely face similar demand shocks within our narrowly defined industries. Under this assumption, equation 2 can be interpreted as identifying the TFP growth gap of SMEs relative to large firms.

Table 2 reports the results of a simple specification with SME indicators and industry $\times$ country fixed effects but excludes X_i. Column 1 shows the result using the full sample. Column 2 to 4 restrict to private firms, manufacturing firms, and non-manufacturing firms, respectively. Consistently across all samples, SME indicators are significantly negative. The bottom of Table 2 shows the results of t-tests comparing the differences between micro and small firms, and between small and medium-sized firms. We find that small firms are statistically different from medium-sized firms while micro and small firms are not statistically different. As a preview to later results, both differences will become statistically different when we control for the full set of covariates.

The result on the sample of private firms (column 2) is quantitatively similar to the full sample. This is not surprising because the vast majority of the sample comprises private firms. Nevertheless, it points to the importance of having a comprehensive sample because using a conventional sample of public firms may miss the evidence on the SME productivity gap. Columns 3 and 4 show that the SME productivity gap is slightly wider for non-manufacturing firms than manufacturing firms. Given that the bulk of literature focuses on public firms and manufacturing firms, our subsample results provide a meaningful benchmark for private and non-manufacturing firms. Overall, these benchmark results not only confirm the visual impression in Figure 1 but also show that the SME productivity gap holds within industry-country groups and is broad-based.

2.4. SME as a distinct vulnerability

Are the SME indicators simply proxies for other firm-level characteristics? To answer this question, we control for an extensive set of covariates and run horseraces of SME indicators against other indicators.

We begin by controlling for the precrisis level of TFP. This control addresses potential heterogeneity across firms because of structural differences in production technology. It also accounts for potential correlation between the growth rate and level of TFP. This correlation may result from productivity convergence when firms that were less productive before the crisis gradually caught up, leading to a negative correlation. It may also result from firms that were more productive before the crisis may continue to grow faster because of growth momentum, leading to a positive correlation.

We then control for life-cycle characteristics (measured by firm age, in linear and quadratic terms). We also include a set of balance sheet indicators—leverage (measured by total liability as a share of total assets), debt maturity (measured by the current liabilities-to-sales ratio, capturing debt maturing in 2008), cash flow, liquidity (measured by cash as a share of total assets), and profitability (measured by the natural logarithm of EBITDA).

Table 3 reports the results. Column 1 offers a benchmark with only SME indicators. Columns 2 to 8 adds other indicators one by one. Column 9 include all except SME indicators. Column 10 reports our preferred specification including all the indicators. We use the same sample across all columns to ensure the horserace is not affected by sample differences. This sample is slightly smaller than the full sample in Table 2 because of data availability in the controls.

We continue to find a negatively significant SME productivity gap across all specifications. Conditional on the full set of covariates, the estimated SME gap becomes wider compared to Table 2. Column 10 shows that the average TFP growth of medium-sized, small, and micro firms was, respectively, 1.1, 2.9, and 5.4 percentage points lower than that of large firms. Notably, these estimates are progressively more negative. The differences between micro and small firms, and between small and medium-sized firms are both statistically significant.

Estimates on the covariates also offer useful information on other predictors of TFP growth. We find a negatively significant coefficient on the level of TFP (columns 2 and 10), consistent with the convergence interpretation. Conditional on the other covariates, firm age enters positively, suggesting that younger firms on average have higher postcrisis TFP growth than older firms (columns 9 and 10). Firms with higher leverage have higher postcrisis TFP growth, yet firms with more debt maturing in 2008 have lower postcrisis TFP growth, consistent with debt overhang (Duval, Hong and Timmer, 2020). Cash flow enters with a negative sign, consistent with the notion that more financially vulnerable firms save more cash with a precautionary motive (Opler et al., 1999).

A comparison across columns 3 to 10 suggests that SME indicators are more robust than balance sheet indicators in predicting postcrisis TFP growth. Overall, the estimates of SME indicators tend to strengthen when controlling for balance sheet indicators, whereas the estimates of balance sheet indicators tend to weaken when controlling for SME indicators.

How much does the SME productivity gap contribute to the total within-firm TFP growth loss after the GFC? We use a back-of-the-envelope calculation to infer the aggregate implications. The average TFP growth loss for large firms in our sample is 3.7 percentage points while our estimated average SME productivity gap is 3.9 percentage points. Taking into account the relative size of precrisis TFP of SMEs and large firms, this in turn implies that the aggregate TFP growth loss of 7.6 percentage points. Therefore, the SME productivity gap may account for 51 percent of the total within-firm TFP growth loss after the GFC.[15]

3. Explaining the SME productivity gap

3.1. Credit market vulnerability

We now turn to testing plausible explanations to this gap. Our starting hypothesis is that the gap was driven by SMEs' vulnerability to tight credit conditions during the crisis. As we discussed earlier, this is motivated by the large and abrupt decline in post crisis TFP growth and theoretical predictions of the uneven impact of credit conditions on SMEs versus large firms. To test this, we exploit variations in the magnitude of the credit supply shock following the collapse of Lehman Brothers on September 15, 2008. This credit supply shock was arguably unforeseen from the firms' perspective and plausibly exogenous to a firm's SME status. If SME productivity is more vulnerable, we should expect the SME productivity gap to be larger in countries where credit conditions tightened more. We estimate the following regression:

$$\begin{aligned} \Delta TFP^{gr}_{ijc} = \alpha_{jc} + \beta_1 Micro_i + \beta_2 Small_i + \beta_3 Medium_i + \delta_1 Micro_i \times \Delta CDS_c \\ + \delta_2 Small_i \times \Delta CDS_c + \delta_3 Medium_i \times \Delta CDS_c + \gamma X_i + \varepsilon_{ijc} \end{aligned} \tag{3}$$

where X_i is the same set of controls as in equation 2. ΔCDS_c is the change in the average CDS spread of domestic banks in country c between September 7 and September 28, 2008 (i.e., 7 days before and after the collapse of Lehman Brothers).[16] Changes in the CDS spread during this period have been used in the literature to proxy for the degree of credit supply shock (Duval, Hong and Timmer, 2020), capturing perceived vulnerabilities of the banks as they tried to protect themselves against the defaults of other banks following Lehman Brothers. Banks whose CDS spread rose more during this period tended to suffer a larger loss in bank capital and faced more difficulty in obtaining funding in the interbank market (Afonso, Kovner and Schoar, 2011; Brunnermeier, 2009). These capital and funding shocks to banks were reflected in tighter credit conditions via a traditional bank lending channel. Under the assumption that firms heavily rely on banks in their home country, the average changes in domestic banks' CDS spreads proxy for the degree of tightening in the aggregate credit conditions faced by domestic firms. This is a reasonable assumption because our sample of European countries is dominated by firms typically without access to foreign banks or nonbank financial markets like corporate bonds or syndicated loans. The reason for measuring changes in the CDS spread in a tight 2-week period surrounding the collapse of Lehman Brothers is that they plausibly reflect credit supply instead of credit demand conditions. Because the real effect of the Lehman Brothers collapse had not materialized during this tight time period, we can also rule out effects resulting from a firm-bank feedback loop. In our estimation, we standardize the change in CDS spread to have mean zero and unit standard deviation. This standardization allows us to interpret the coefficient as the effect of a tighter credit supply condition on the TFP growth of the average firm in the average country.

[15]The average TFP growth loss for large firms is calculated as a weighted average of firm-level post minus precrisis TFP growth, weighted by precrisis TFP. Repeating the baseline (Table 3 column 10) with a weighted regression using precrisis TFP as weights, we find a weighted gap for medium-size, small, and micro firms to be 1.1, 2.9, and 5.4 percentage points, respectively. Weighting them by precrisis TFP gives the average SME productivity gap.

[16]Our data source is the 5-year CDS spread from the Markit database. The CDS spread is expressed in units of basis points. See Figure A2 for the CDS spread around the collapses of Lehman Brothers.

We further sharpen the identification by replacing the change in the average CDS spread in the firm's home country with the change in the average CDS spread of the firm's main creditor banks. This specification exploits variations in the firm-bank relationship and allows us to rule out confounding factors that may be correlated with average change in CDS spread at the country level. As before, we standardize the change in CDS spread to have mean zero and unit standard deviation.

Table 4 column 1 shows results using the country-level change in CDS spread. The coefficient of the interaction of SME indicators and change in the CDS spread are significantly and robustly negative, indicating that SMEs experience a larger decline in TFP growth vis-à-vis large firms in countries where credit conditions tightened more. The interaction terms are also progressively more negative for medium-sized, small, and micro firms, indicating that the credit supply shock has progressively larger effects on medium-sized, small, and micro firms. The results are economically significant. In a country where the increase in the CDS spread was one standard deviation higher than the average country, the TFP growth for medium-sized, small, and micro firms was, respectively, 2.5, 5.0, and 7.5 percentage points lower than for large firms. For firms in a country with the average increase in CDS spread, the gap was respectively 1.2, 2.6, and 4.8 percentage points.

Column 2 shows results using the firm-level change in the CDS spread. Compared to regressions using aggregate CDS information, using firm-level CDS information leads to a reduction of the sample; nevertheless, the coefficients of the interaction terms remain significant. They are again progressively more negative for medium-sized, small, and micro firms.

These results are consistent with SMEs' vulnerability to adverse credit supply shocks. Why? We investigate two specific mechanisms: creditor strength and relationship banking. Having strong creditors that can weather the crisis relatively well is an important mitigating factor for borrowers. We hypothesize that having stronger creditor banks mitigates the shock and reduces the SME productivity gap. We estimate the following regression:

$$\begin{aligned}\Delta TFP^{gr}_{ijc} = \alpha_{jc} + \beta_1 Micro_i + \beta_2 Small_i + \beta_3 Medium_i + \delta_1 Micro_i \times BankStrength_b \\ + \delta_2 Small_i \times BankStrength_b + \delta_3 Medium_i \times BankStrength_b + \gamma X_i + \varepsilon_{ijc}\end{aligned} \tag{4}$$

We use two alternative measures of bank strength. The first captures bank capitalization, defined as a dummy variable that takes a value of 1 if the average precrisis regulatory Tier 1 capital (in percentage of Risk-Weighted Assets) of a firm's creditor banks is above the median. The literature has shown that the level of capitalization can be a driver of bank performance during the crisis (Berger and Bouwman, 2013; Beltratti and Stulz, 2012; Kapan and Minoiu, 2018). The second measure captures a bank's presence in the CDS market. To the extent that banks traded on the CDS market are larger and have stronger fundamentals, a bank's presence in the CDS proxies for bank strength. Exploring the bank strength channel comes at the cost of a sample reduction because of the data availability of firm-bank relationships, bank capitalization, or CDS presence. Nevertheless, results from this smaller sample can usefully show the direct link from ex-ante creditor strength to the firms' TFP growth. We include the same set of controls as in equation 2.

Table 4 column 3 shows results with bank capitalization. The coefficients of the interaction of SME indicators and bank strength are positive, consistent with stronger creditor banks mitigating the SME productivity gap. The estimates are especially large for micro and small firms. Among firms with low-capitalized banks, the TFP growth of medium-sized, small, and micro firms are respectively 2.3, 5.4, and 8.1 percentage points lower than large firms. Among firms with high-capitalized banks, the gap is reduced to 2.2, 2.6, and 5.0 percentage points, respectively. Results in column 4 derived from the CDS presence measure are similar.

The second mechanism we investigate is relationship banking. The literature has shown that, by using proprietary information about their borrowers, relationship banks can more easily adapt their lending conditions during a crisis than transaction banks, thus mitigating the effect of adverse credit shocks to the borrowers (Beck et al., 2018). To the extent that SMEs have a greater reliance on relationship banks, we expect the SME productivity gap to be larger in places where relationship banks are less a presence. We use data from the Banking Environment and Performance Survey, which classifies banks as relationship or transaction banks based on face-to-face interviews with bank chief executive officers. The data are available for 5 countries in our sample: Czech Republic, Estonia, Poland, Slovakia, and Slovenia. For each country, we measure relationship bank presence by relationship banks as a share of total banks.

Table 4 column 5 shows the results. The SME indicators are again significantly negative. The coefficient of the interaction of SME indicators and relationship bank presence are positive and economically large. A one standard deviation in the share of relationship banks (i.e., 22.5 percent) reduces the productivity gap by 4.3 percentage points for micro firms, by 3.3 percentage points for small firms, and by 1.4 percentage points for medium-sized firms. This result is consistent with the notion that relationship banks mitigate the productivity gap and more so for firms that are more vulnerable to adverse credit market shocks.

We interpret our results in this subsection as reflecting an ex-ante credit market vulnerability of SMEs for the following reasons. Given the persistence of SME status and the unforeseeable nature of the shock, the likelihood that a firm would switch from an SME to a large firm (or vice versa) in anticipation of a crisis is very low.[17] Moreover, as Figure 1 shows, the TFP of SMEs did not on average grow at a rate slower than that of large firms before the crisis, supporting the parallel trend assumption of our DID model.

3.2. Testing alternative explanations

In this section, we ask whether the SME productivity gap can also be attributable to alternative explanations.

3.2.1. Management quality

Following the seminal work of (Ichniowski, Shaw and Prennushi, 1997), a number of papers have suggested management quality as a driver of TFP growth. The adoption of management best practices can improve production efficiency and labor quality (Bloom and Van Reenen, 2007; Bender et al., 2018). One may wonder whether the SME productivity gap may be due to large firms improving their management quality more than SMEs after the crisis (i.e., an SME management quality gap). To test this hypothesis, we use data from the World Management Survey (WMS) as described and analyzed in Bloom and Van Reenen (2007) and Bloom et al. (2014). The survey evaluates the management quality of firms and organizations on performance monitoring, target setting, and incentive management. The double-blind survey technique and randomized sampling facilitate the comparison of the scores across industries and countries.

We first examine the aggregate time trend. Figure A3 shows that the management quality of large firms did not improve more than that of SMEs after the crisis. We then exploit cross-sectional heterogeneity. If the SME productivity gap is attributable to management quality, we would expect the gap

[17] Table A1 shows that in our sample 99.5 percent of SMEs before the crisis remained such after the crisis.

to be larger in countries or industries where the postcrisis management quality of large firms improved more vis-à-vis SMEs. We find no evidence supporting this hypothesis. In Table A2 columns 3 and 4, we classify country–industry groups according to whether the postcrisis management quality improvement of large firms vis-à-vis SMEs is high (i.e., above the median) or low. We find that the SME productivity gap does not vary along this dimension.

Figure A3 also shows that SMEs have on average lower management quality than large firms. One may wonder whether the initial level of management quality matters (e.g., because of quality convergence or momentum reasons). To test this hypothesis, we classify country–industry groups by their precrisis level of management quality in Table A2 columns 1 and 2. We find no evidence that the SME productivity gap varies along this dimension. Over all, these results suggest that the SME productivity gap is unlikely to be driven by management equality. One caveat is that, although we are able to test the role of management quality as measured by the WMS, we are silent about the role of unmeasured management quality. In Section 4.1, we will address this with a general framework of intangible capital. The framework is useful because management quality can be broadly considered as part of a firm's intangible capital (Bloom, Sadun and Van Reenen, 2016; Corrado, Hulten and Sichel, 2005).

3.2.2. Market power

Recent literature shows that rising market power could lead firms to invest less and weaken productivity growth (IMF, 2019; Akcigit and Ates, 2021). Yet its implication for the SME productivity gap is a priori ambiguous. On one hand, rising market power implies large firms growing larger and acquiring more power, weakening their incentives to engage in productivity-enhancing activities. On the other hand, rising market power enables large firms to recoup fixed costs or reward them for the higher risks associated with large investment. We use two complementary approaches to test these implications. First, we explore the cross–industry heterogeneity of market concentration. Following IMF (2019), we measure market concentration by the sales of the top 8 firms as a share of the top 20 firms at the country–industry level. In Table A4 column 1, we find that the productivity gap for medium-sized firms does not vary with market concentration. The gap for micro and small firms is slightly (10–17 percent) smaller in industries with a high market concentration (i.e., above the median of the sample) than those with a low market concentration. The difference is marginally significant (at the 10 percent level).

A recent literature points out that price markups—the ratio of a good's price to the marginal cost of producing it—are a better gauge of market power than market concentration. Our second approach explores the role of markups in firm-level productivity. We compute markups for each firm following the definition in De Loecker and Warzynski (2012) and the estimation procedure in Diez, Fan and Villegas-Sánchez (2019). Table A3 columns 3 to 6 show the results controlling two alternative measures of markups estimated with different production functions. We continue to find a large SME productivity gap after the control. The estimated gap for micro and small firms are quantitatively very close to the baseline. For medium-sized firms, it ranges from 1.5 percent to 1.7 percent, compared to 1.1 percent in the baseline. Overall, we interpret these results as evidence against market power as a key driver of the SME productivity gap. If anything, market power may have contributed to reducing the productivity gap of medium-sized firms relative to large firms.

3.2.3. Technological leadership

A recent literature (Akcigit and Ates, 2021; Aghion et al., 2019) argues that the advancement of information and communication technology and a decline in technology diffusion from leaders to followers could contribute to a divergence in firm growth. Does the SME productivity gap simply reflect the growth premium of leader firms? To investigate this hypothesis, we include a firm-level measure of leader firms following (Akcigit and Ates, 2021), defined as firms whose precrisis TFP was above the 90th percentile. Table A3 column 1 and 2 shows the results. Including this control does not affect our results. In column 1, the coefficients of the SME indicators remain significant and are similar to the baseline (Table 3 column 10). In column 2, the coefficients on the interaction of SME indicators and changes in CDS spreads are also similar to before (Table 4 column 1).

3.2.4. Resource misallocation

The literature suggests that resource misallocation is an impediment to TFP growth. The idea is that when the marginal product of inputs is not equalized across firms, aggregate productivity would be higher if resources were reallocated from firms with a lower marginal product to firms with a high marginal product (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). A priori, resource misallocation is unlikely to drive the SME productivity gap because large firms have a higher productivity on average. If anything, misallocation likely impedes the productivity growth of large firms more than that of SMEs. To test this hypothesis formally, we exploit cross-sectional variations in misallocation across industries, noting that capital and labor are difficult to be reallocated in the short run. To the extent that misallocation drives the SME productivity gap, we expect the gap to be wider in industries with severer misallocation. We follow Hsieh and Klenow (2009) and measure misallocation with the precrisis dispersion in the marginal products of capital and labor (i.e., TFPR dispersion) at the country–industry level. Table A4 column 2 shows that the SME productivity gap does not systematically differ between industries with a high (i.e., above median) and low level of misallocation.

3.2.5. Productivity bottleneck

Yet another impediment to TFP growth is a productivity bottleneck. The idea is that a technological advancement requires a simultaneous improvement in complementary inputs, the lack of which––—potentially caused by the bottleneck induced by the original advancement——may impede growth. Following (Acemoglu, Autor and Patterson, 2021), we measure the bottleneck of an industry by the dispersion in the supplier industries' productivity growth. Table A4 column 3 shows that the gap for small and medium-sized firms does not vary with the size of the bottleneck. For micro firms, the SME productivity gap in industries with a high level of bottleneck is 9 percent smaller than in industries with a lower level of bottleneck. The difference is marginally significant (at the 10 percent level).

3.3. Discussion

We have tested a number of alternative explanations to the SME productivity gap. We find strong evidence in support of the SME's credit market vulnerability. For the other explanations, the gap is only marginally related to market concentration and productivity bottlenecks for micro or small firms. Even in these cases, the results are much weaker compared to those for the credit market channel in terms of statistical and economic significance, suggesting that the SME productivity gap is unlikely to be driven by these alternative channels.

For a final piece of evidence, we examine whether any of these channels may explain variations in the SME productivity gap at the country level. Figure A4 summarizes results of country-level regressions on credit market conditions (panel A), management quality (panel B), market concentration (panel C), resource misallocation (panel D), and productivity bottlenecks (panel E). We find a strong relationship between the SME productivity gap and the tightening of credit conditions, consistent with findings in Section 3.1. On the other hand, we find no evidence that the SME productivity gap varies with other dimensions, further collaborating firm- or industry-level results in Section 3.2.

4. Extensions and robustness

4.1. Intangible capital

Following the seminal work of Corrado, Hulten and Sichel (2005), a growing literature has shown that intangible capital—such as brand recognition, firm-specific human capital, and management quality—is an important input to production. Under this view, part of the TFP (as conventionally defined in equation 1) reflects intangible capital input. Therefore a larger postcrisis decline in SME's intangible capital vis-à-vis large firms (i.e., an SME intangible capital gap) would be consistent with an SME productivity gap. We start with two tests on this hypothesis and discuss the relationship between intangible capital and TFP growth in the second half of this section.

First, if intangible capital plays a role in the SME productivity gap, we expect the gap to be larger in industries that are more intangible intensive. We test this hypothesis using two alternative measures of intangible intensity: intangible capital as a share of total assets and the number of patent applications. Our data source for patent application is PATSTAT, maintained by the European Patent Office. PATSTAT is the most comprehensive cross-country patent database, containing bibliographic data on patents from 90 patent-issuing authorities, covering close to the population of all patents worldwide. We match applicant firms from PATSTAT to firms in the Orbis dataset using firm-patent matches provided by Bureau van Dijk. We define an industry as intangible intensive if its intangible intensity is above the median in the precrisis period. Table 5 columns 1 and 2 show that the coefficients of the interaction of intangible intensity and SME indicators are significantly negative with both measures. This suggests that the SME productivity gap is wider in intangible intensive industries than in other industries. The results are economically large. For example, the gap between micro and large firms is 192 percent wider in intangible intensive industries than other industries based on the intangible capital share measure (column 1); it is 224 percent wider based on the patent application measure (column 2).

Second, models of the cyclical composition of investment predict that negative liquidity shocks make firms less willing to engage in long term investment (Aghion et al., 2010). Investment in intangible capital is productivity enhancing but takes longer to materialize than investment in physical capital. We test these implications by estimating the following regression:

$$\Delta Investment_{ijc} = \alpha_{jc} + \beta_1 Micro_i + \beta_2 Small_i + \beta_3 Medium_i + \gamma X_i + \varepsilon_{ijc} \tag{5}$$

As in equation (2), Δ measures the average difference between the pre- (2004–2007) and postcrisis (2008–2011) periods whereas $Investment$ is either intangible investment as a share of total investment or the number of patent applications. As in equation 2, we include industry–country fixed effects and a set of covariates. We also control for the precrisis level of the dependent variable. This is in the same spirit of the TFP level control in equation 2 and addresses the potential confounding factor that change in investment may be related to its level for reasons unrelated to the crisis.

Table 5 column 3 shows that SMEs reduced their intangible investment as a share of total investment more than large firms after the crisis. The estimated gap is significantly negative at -1.7, -2.0, and -2.7 percentage points for medium-sized, small, and micro firms, respectively. These estimates are economically large given that SME's intangible investment is on average only 9 percent of total investment before the crisis.

Column 4 shows results on patent applications. For this analysis, we restrict to the sample to firms that ever filed a patent application, so the result comes at a cost of a large reduction of the sample. Notwithstanding the smaller sample, the results are informative because it is representative of patenting firms. We find that SMEs reduced their patent applications more than large firms after the crisis. The average reduction is 0.27 patent per year for micro firms, 0.21 for small firms, and 0.19 for medium-sized firms, all relative to large firms. Although these differences might seem small in their absolute magnitudes, they are in fact economically very large for two reasons. First, the average patent application was only 0.45 per year for SMEs and 0.47 for all firms. Our results suggest that a large majority of new patents are lost for SMEs in the postcrisis period. Second, the literature suggests that patents have substantial value in a firm's subsequent growth and funding access, especially for firms with a small number of patents (Farre-Mensa, Hegde and Ljungqvist, 2020). Data availability prevents us from estimating patent values, but taking patent valuation into account likely aggravates the patenting gap, considering that SMEs on average have fewer patents than large firms.

One may be concerned that tax incentives for intangible investment may drive the SME intangible gap if SMEs and large firms are subject to different incentives. Comprehensive data on R&D tax incentives from OECD (2021) show that only four countries in our sample had differential tax incentives for SMEs and large firms. Figure A5 shows no systemic postcrisis trend on these differential treatments. The tax subsidy rate for SMEs increased vis-à-vis large firms in the United Kingdom and Netherlands, but not in France and Norway. To formally test the role of these tax incentives, we calculated an SME tax subsidy gap, defined as the postcrisis change in tax incentives for SMEs vis-à-vis large firms, in the spirit of the SME productivity gap. Table A11 shows no evidence that the SME intangible gap varies systematically with the SME tax subsidy gap.

We now turn to quantifying how much of the SME productivity gap shown in Section 2 can be explained by intangible capital. We draw inference by comparing TFP growth from two alternative forms of production functions. The first form follows a large literature that dates back to Solow (1957) and assumes a production function with physical capital and labor: $Y = AK^{\beta_k}L^{\beta_l}$, where Y, K, and L are value-added output, physical capital, and labor respectively. TFP growth calculated with this production function, which we refer to as a Solow measure, reflects output growth not explained by physical capital and labor growth. Our estimation equation 1 is based on this form. The second form follows a growing literature on intangible capital and assumes a production function with intangible capital: $VA = A'(IK)^{\beta_{ik}}K^{\beta_k}L^{\beta_l}$, where IK is intangible capital. TFP growth calculated with this production function, which we refer to as an intangible-augmented measure, reflects output growth not explained by physical capital, intangible capital, and labor growth.

An accounting identify exists between these two TFP growth measures. The interpretation is quite intuitive: By excluding intangible capital as an input, the Solow measure attributes the contributions from intangible capital growth to output growth as contributions from TFP growth. The exclusion of intangible capital in the Solow measure also leads to different estimates of physical capital and labor shares, and thus affects the output growth attributable to physical capital and labor growth. We summarize the results of a decomposition exercise in Table A5.[18] In the spirit of equation 2, the SME productivity gap is defined as the difference between large firms' and SMEs' postcrisis reduction of TFP growth, which we now aggregate using output-weighted averages of firm-level estimates. In the same spirit, we calculate the SME labor gap, physical capital gap, intangible capital gap, and out-

[18] See online Appendix for details.

put gap. Our results show that, under the Solow measure, the SME productivity gap contributes 13 percent of the SME output gap. Labor and physical capital gap contribute the remaining 60 and 28 percent, respectively. Under the intangible-augmented measure, SME productivity, labor, physical capital, and intangible capital gap contribute 13, 59, 25, and 0.4 percent of the SME output gap, respectively. Finally, the portion of the SME productivity gap under the Solow measure attributable to intangible capital can be calculated by adding the contribution from intangible capital gap and estimation adjustment for physical capital and labor. This suggests that intangible capital explains 21 percent of the SME productivity gap under the Solow measure.

4.2. Robustness

In this section, we test the robustness of our results with respect to alternative measurements, samples, and specifications.

4.2.1. Credit market measures

We perform two robustness tests on the credit market measures. We first measure creditor strength using the top bank (the first bank in AMADEUS's BANKER variable) instead of taking averages of the firm's main creditor banks. Our results (Table A6 columns 1 and 2) are very similar to those obtained earlier.

We then explore alternative measures of credit market conditions using the euro area Bank Lending Survey (BLS) from the European Central Bank. The BLS is addressed to senior loan officers of a representative sample of banks. We use the survey response on changes in credit standards to measure credit supply conditions. Credit standards are the internal guidelines for loan approval and loan terms. Higher credit standards reflect a tighter credit supply. One advantage of the BLS measure compared to the CDS spread data is that it separates loan supply factors from loan demand factors. Thus, we can reasonably rule out demand-side factors and the firm-bank feedback loop. Furthermore, the BLS distinguishes corporate credit from household credit, allowing us to focus on credit conditions for firms. Because the BLS is available quarterly, we use changes in the loan supply conditions in the last quarter of 2008 to measure the crisis shock.[19] In comparison, the CDS spread data are available daily, allowing us to measure changes in credit condition over a very tight window to rule out demand factors and the firm-bank feedback loop. Because of these relative advantages of the BLS and CDS data, we view these two measures as complementary.

The results with the BLS measure confirm the role of tighter credit market conditions (Table A6 columns 3 and 4).[20] The coefficient of the interaction of SME indicators and credit tightening is significantly and robustly negative. Therefore, our results hold more generally for other measures of credit conditions and are not driven by the CDS data.

[19] We use this period because the most acute phase of the crisis occurred right after the collapse of Lehman Brothers on September 15, 2008.

[20] The results include five countries for which the BLS is available: France, Germany, Netherlands, Portugal, and Spain. The BLS measures changes in credit condition with a "diffusion index", which is the weighted difference between the share of banks reporting that credit standards have been tightened and the share of banks reporting that they have been eased. A high index indicates more tightening. In unreported results, we obtained similar findings using a "net percentage" measure, calculated as the unweighted difference between the share of banks reporting that credit standards have been tightened and the share of banks reporting that they have been eased.

4.2.2. Country sample

We investigate the robustness of our estimates on the SME productivity gap with respect to the country sample. First, we note that the gap is not homogeneous across the countries. It was larger in southern European countries than the rest of the sample (Table A7). This finding is fully consistent with the credit market explanation in Section 3.1 because these countries were hit hardest by the crisis. Second, despite country heterogeneity, the overall finding on the SME productivity gap is not driven by a single country. Repeating the baseline regression but excluding one country at a time leads to similar results (Table A8). Neither are these results driven by countries with more firms in the sample. Repeating the same exercise but weighting all countries equally also leads to similar results (Table A9).

Can the aggregate implications of our results be generalized to other European countries? The lack of data does not allow us to estimate the SME productivity gap in all the countries, yet an indirect inference is possible by comparing the contribution of SMEs in our sample of countries to that in other European countries. Table A12 shows that SMEs as a share of the aggregate economy (in terms of employment and gross output) in our 18-country sample is very close to that in all EU countries.

4.2.3. Subsample periods

Our baseline sample includes four years in the postcrisis period (2008-2011) to allow for a sluggish TFP response to the crisis. The latter part of the sample period coincides with the European sovereign crisis. One may wonder whether the sovereign debt crisis may have different implications for SME productivity. To test this hypothesis, we separately estimate the baseline regression while defining the postcrisis period as the the sovereign debt crisis period (2010-2012) or the immediate aftermath of the GFC (2008-2009). We find that the SME productivity gap exists in both sample periods. The gap was wider in the immediate aftermath of the GFC than during the sovereign debt crisis period (Table A10 columns 2 and 3). This evidence is also supportive of the view that the GFC shock is a key driver of the SME productivity gap.

4.2.4. The recession in 2000

We further analyze the extent to which our results reflect the unique challenge of the GFC. Our point of comparison is the recession in 2000 after the burst of the dot-com bubble. Unlike the GFC, this recession was not associated with a negative credit supply shock, hence we do not expect to find an SME productivity gap during this period to vary with credit conditions. To test this, we run equations 2 and 4 with bank capitalization but replace the years pre- and post-GFC with years pre- and post-2000.[21] Table A13 shows that TFP growth following the 2000 recession was not associated with SME indicators and their interactions with credit conditions.

4.2.5. Sample attrition

Figure A1 shows that the coverage of the Orbis data relative to the Eurostat Structural Business Statistics (SBS) changes for some countries over the sample period. One may be concerned that sample attrition may be driving our results. To check the robustness of our results with respect to potential sample attrition, we repeat our exercise but limit to a subset of countries with stable coverage over our sample period. Our results are robust to using this subsample (Table A10 column 1).

[21] We focus on bank capitalization because CDS data were limited for this period. We include firms in five countries in this test—France, Germany, Netherlands, Spain, and the United Kingdom—that have available data.

4.2.6. Entry and exit

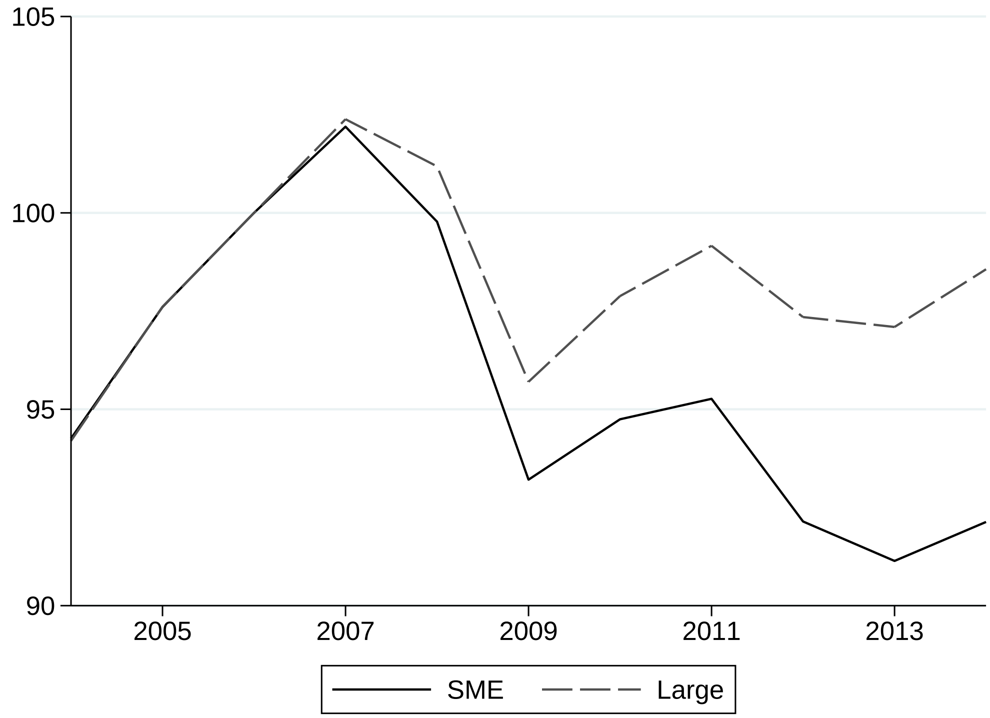
Our results so far are based on a balance sample of firms during our sample period. As discussed earlier, we exclude firms that enter or exit to avoid confounding productivity drivers with firm entry and exit. Nevertheless, our approach is readily applicable to all firms. As an extension, we estimate our regressions with all the firms including those that enter and exit the data during our sample period. Table A10 column 4 shows the results. We continue to find an SME productivity gap, of slightly larger magnitude than the baseline estimates in Table 3.

5. Conclusion

Productivity growth in Europe has been persistently slow since the GFC. In this paper, we examine the crisis impact on firm-level productivity drawing on the GFC experience. Using a comprehensive firm-level data for European countries, we find new evidence of an uneven impact: SMEs experienced a larger decline in postcrisis TFP growth vis-à-vis large firms. The impact was progressively larger for medium, small, and micro firms relative to large firms. It was also disproportionately larger for firms facing a more severe tightening of credit conditions. Our results highlight the SMEs' credit market vulnerability to the adverse credit supply shock as an impediment to their postcrisis productivity growth.

6. Figures

Figure 1: TFP level path for SMEs and large firms



Notes: This figure plots the average firm-level TFP for SMEs and large firms calculated from the Orbis database. Firm-level TFP is calculated using the Wooldridge (2009) method by estimating equation 1. The TFP level in 2006 is normalized to 100. The vertical axis represents the TFP level relative to the base year (%). We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total.

7. Tables

Table 1: Summary statistics on firms

	Obs	Mean	St. Dev.	Min	Median	Max
ΔTFP growth (Baseline)	701,613	-0.05	0.21	-5.87	-0.04	8.32
TFP	701,613	0.02	0.13	-7.84	0.02	5.87
Micro	701,613	0.53	0.50	0.00	1.00	1.00
Small	701,613	0.34	0.47	0.00	0.00	1.00
Medium	701,613	0.10	0.30	0.00	0.00	1.00
Age	667,175	18.79	11.86	4.00	16.00	192.00
Leverage	667,175	0.63	0.24	0.02	0.66	7.35
Debt Maturity	667,175	0.44	0.68	0.00	0.29	16.39
Cash Flow	667,175	0.11	0.09	-0.29	0.09	1.69
Liquidity	667,175	2.32	32.52	0.11	1.40	4,973.77
Profitability	667,175	11.57	1.68	6.22	11.50	19.30
ΔIntangible investment share	562,924	-0.01	0.27	-1.00	0.00	1.00
Intangible investment share	562,924	0.09	0.26	-1.00	0.00	1.00
ΔPatent Applications	4,824	0.05	0.97	-2.00	0.00	3.00
Patent Applications	4,824	0.47	0.65	0.00	0.25	3.00
ΔCDS (Country-level)	13	0.16	0.06	0.07	0.17	0.27
ΔCDS (Firm-level)	56,832	0.32	0.18	-0.00	0.29	1.51
Tier 1 Capital Ratio	28,593	0.10	0.03	0.09	0.10	0.34
CDS Presence	221,096	0.27	0.44	0.00	0.00	1.00
Relationship Bank Share	5	0.43	0.22	0.22	0.31	0.67

Notes: ΔTFP growth is the change in the average TFP growth between the postcrisis (2008–2011) minus precrisis (2004–2007) periods. TFP is the precrisis productivity level. *Micro*, *Small*, and *Medium* are dummy variables for micro, small, and medium-sized firms, classified using the EU definition. *Age* is the firm's age as of 2007, *Leverage* is liability to assets, *Debt maturity* is current liabilities to sales, *Cash flow* is operating cash flow to assets, *Liquidity* is cash to assets, and *Profitability* is log EBITDA, all precrisis values. *Intangible investment share* is the firm's intangible investment as a share of intangible and physical investment. *Patent applications* is the firm's total number of annual applications. ΔCDS (Country-level) is the change in the average 5-year CDS spread of domestic banks in each country between 7 days before and after the collapse of Lehman Brothers. ΔCDS (Firm-level) is the average ΔCDS among the firm's main creditor banks. *Bank capital* is the average precrisis regulatory Tier 1 capital ratio of a firm's creditor banks. *CDS presence* is a dummy equal to one if a firm's creditor bank was present in the CDS market prior to the Lehman Brother collapse. *Relationship bank share* is the share of bank branches in each country that are from relationship banks.

Table 2: SME productivity gap

	(1) Full Sample	(2) Private	(3) Manufacturing	(4) Non-manufacturing
Micro	-0.0103***	-0.0100***	-0.0065*	-0.0121***
	(0.0020)	(0.0020)	(0.0036)	(0.0023)
Small	-0.0103***	-0.0100***	-0.0048	-0.0126***
	(0.0018)	(0.0018)	(0.0034)	(0.0022)
Medium	-0.0072***	-0.0068***	-0.0018	-0.0094***
	(0.0017)	(0.0017)	(0.0033)	(0.0020)
Observations	701,613	700,642	143,250	558,363
R^2	0.05	0.05	0.06	0.05
Mean dep var	-0.05	-0.05	-0.05	-0.05
Lag TFP control	No	No	No	No
Balance sheet controls	No	No	No	No
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes
Micro = Small (p-val)	1.00	0.99	0.20	0.71
Small = Medium (p-val)	0.00	0.00	0.06	0.02

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table 3: Horseraces

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Micro	-0.0141***	-0.0095***	-0.0114***	-0.0158***	-0.0150***	-0.0263***	-0.0141***	-0.1360***		-0.0541***
	(0.0020)	(0.0013)	(0.0020)	(0.0020)	(0.0022)	(0.0023)	(0.0020)	(0.0039)		(0.0027)
Small	-0.0120***	-0.0004	-0.0109***	-0.0136***	-0.0130***	-0.0255***	-0.0120***	-0.0927***		-0.0288***
	(0.0018)	(0.0012)	(0.0018)	(0.0019)	(0.0021)	(0.0021)	(0.0018)	(0.0031)		(0.0021)
Medium	-0.0088***	0.0023**	-0.0087***	-0.0101***	-0.0096***	-0.0220***	-0.0088***	-0.0486***		-0.0105***
	(0.0017)	(0.0011)	(0.0017)	(0.0018)	(0.0018)	(0.0020)	(0.0017)	(0.0021)		(0.0014)
TFP		-1.2146***							-1.2109***	-1.2078***
		(0.0039)							(0.0039)	(0.0037)
Age			0.0009***						-0.0003***	-0.0005***
			(0.0001)						(0.0000)	(0.0000)
Leverage				-0.0075***					0.0399***	0.0334***
				(0.0018)					(0.0016)	(0.0015)
Debt Maturity					-0.0016				-0.0036***	-0.0026***
					(0.0014)				(0.0008)	(0.0008)
Cash Flow						-0.3268***			-0.0759***	-0.0375***
						(0.0101)			(0.0059)	(0.0071)
Liquidity							0.0000**		0.0000	0.0000
							(0.0000)		(0.0000)	(0.0000)
Profitability								-0.0279***	-0.0035***	-0.0107***
								(0.0007)	(0.0004)	(0.0006)
Observations	667,175	667,175	667,175	667,175	667,175	667,175	667,175	667,175	667,175	667,175
R^2	0.05	0.60	0.05	0.05	0.05	0.07	0.05	0.07	0.60	0.61
Mean dep var	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
Lag TFP control	No	Yes	No	No	No	No	No	No	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.03	0.00	0.59	0.02	0.04	0.42	0.03	0.00		0.00
Small = Medium (p-val)	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00		0.00

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. *Age* is the firm's age as of 2007, *Leverage* is liability to assets, *Debt maturity* is current liabilities to sales, *Cash flow* is operating cash flow to assets, *Liquidity* is cash to assets, and *Profitability* is log EBITDA, all precrisis values. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table 4: Credit market vulnerability

	(1) ΔCDS (Country-level)	(2) ΔCDS (Firm-level)	(3) Bank Capital	(4) CDS Presence	(5) Relationship Bank Share
Micro	-0.0480***	-0.0476***	-0.0811***	-0.0647***	-0.1494***
	(0.0025)	(0.0036)	(0.0076)	(0.0040)	(0.0173)
Micro × Credit	-0.0276***	-0.0062**	0.0309**	0.0115***	0.1882***
	(0.0042)	(0.0026)	(0.0136)	(0.0042)	(0.0299)
Small	-0.0261***	-0.0242***	-0.0543***	-0.0405***	-0.1105***
	(0.0021)	(0.0029)	(0.0063)	(0.0031)	(0.0130)
Small × Credit	-0.0242***	-0.0049**	0.0279***	0.0121***	0.1479***
	(0.0033)	(0.0020)	(0.0104)	(0.0034)	(0.0220)
Medium	-0.0124***	-0.0110***	-0.0237***	-0.0183***	-0.0469***
	(0.0017)	(0.0023)	(0.0053)	(0.0025)	(0.0087)
Medium × Credit	-0.0132***	-0.0041**	0.0014	0.0040	0.0600***
	(0.0025)	(0.0016)	(0.0088)	(0.0030)	(0.0150)
Credit		0.0155**	-0.0029	-0.0297***	
		(0.0071)	(0.0377)	(0.0107)	
Observations	209,175	56,832	28,593	221,096	34,561
R^2	0.63	0.67	0.61	0.63	0.65
Mean dep var	-0.04	-0.04	-0.06	-0.05	-0.06
Lag TFP control	Yes	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. Each column uses different measures of *Credit* as indicated in the column header. ΔCDS (Country-level) is the change in the average 5-year CDS spread of domestic banks in each country between 7 days before and after the collapse of Lehman Brothers. ΔCDS (Firm-level) replaces the change in the average CDS spread in the firm's home country with the change in the average CDS spread of the firm's main creditor banks. We standardize the change in CDS spread to have mean zero and unit standard deviation. *Bank capital* is a dummy variable equal to one if the average precrisis regulatory Tier 1 capital (in percentage of Risk-Weighted Assets) of a firm's creditor banks is above the median. *CDS presence* is a dummy variable equal to one if a firm's creditor bank was present in the CDS market prior to the Lehman Brother collapse. *Relationship bank share* is the number of branches of relationship banks in each country as a share of the total number of bank branches, constructed using the Banking Environment and Performance Survey. The survey covers countries in Eastern Europe including Czech Republic, Estonia, Poland, Slovakia, and Slovenia. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

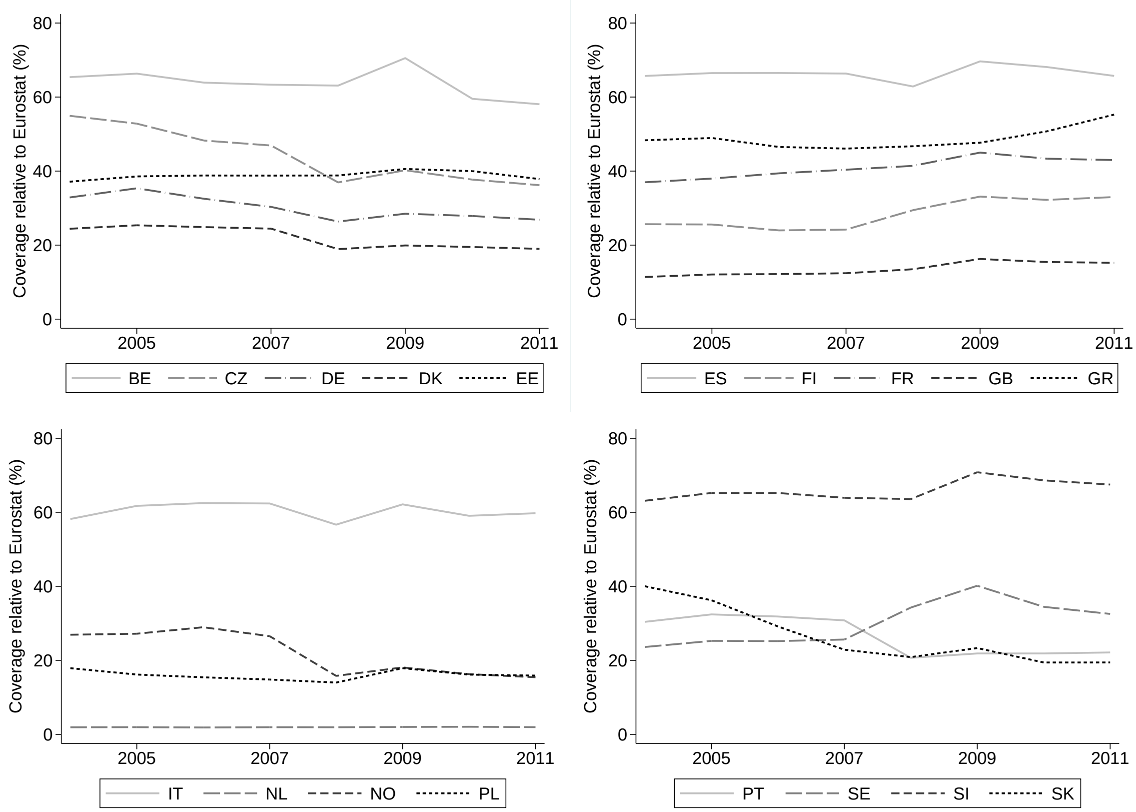
Table 5: SME intangible capital gap

Industry Intensity	High Intangible Share	High Patent Applications		
Dependent Variable	ΔTFP Growth (1)	ΔTFP Growth (2)	Δ Intangible Investment Share (3)	Δ Patent Applications (4)
Micro	-0.0331***	-0.0416***	-0.0268***	-0.2890***
	(0.0037)	(0.0049)	(0.0032)	(0.0750)
Micro × Industry Intensity	-0.0304***	-0.0518***		
	(0.0048)	(0.0103)		
Small	-0.0165***	-0.0190***	-0.0201***	-0.2226***
	(0.0027)	(0.0039)	(0.0029)	(0.0564)
Small × Industry Intensity	-0.0193***	-0.0472***		
	(0.0037)	(0.0085)		
Medium	-0.0058***	-0.0026	-0.0164***	-0.2012***
	(0.0021)	(0.0029)	(0.0027)	(0.0496)
Medium × Industry Intensity	-0.0086***	-0.0350***		
	(0.0027)	(0.0063)		
Observations	667,125	191,407	562,924	4,824
R^2	0.61	0.58	0.28	0.47
Mean dep var	-0.054	-0.056	-0.007	0.047
Lag dep var	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes

Notes: Each dependent variable is the difference in the average between the pre- and postcrisis periods. *Intangible investment share* is the firm's intangible investment as a share of intangible and physical investment. We use the firm's reported intangible assets to construct intangible investment. We estimate physical capital by applying the perpetual inventory method to each firm's book value of fixed tangible assets and depreciation. *Patent applications* is based on the firm's total number of annual applications each year from the Worldwide Patent Statistical Database (PATSTAT). Columns (1) and (2) uses two different measures of an industry's intensity of intangible capital. We classify a firm as *High Intangible share* if the firm's (4-digit) industry had an average share of intangible investment to total investment ratio below the median across industries. *High Patent applications* is defined similarly based on the firm's annual patent applications. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

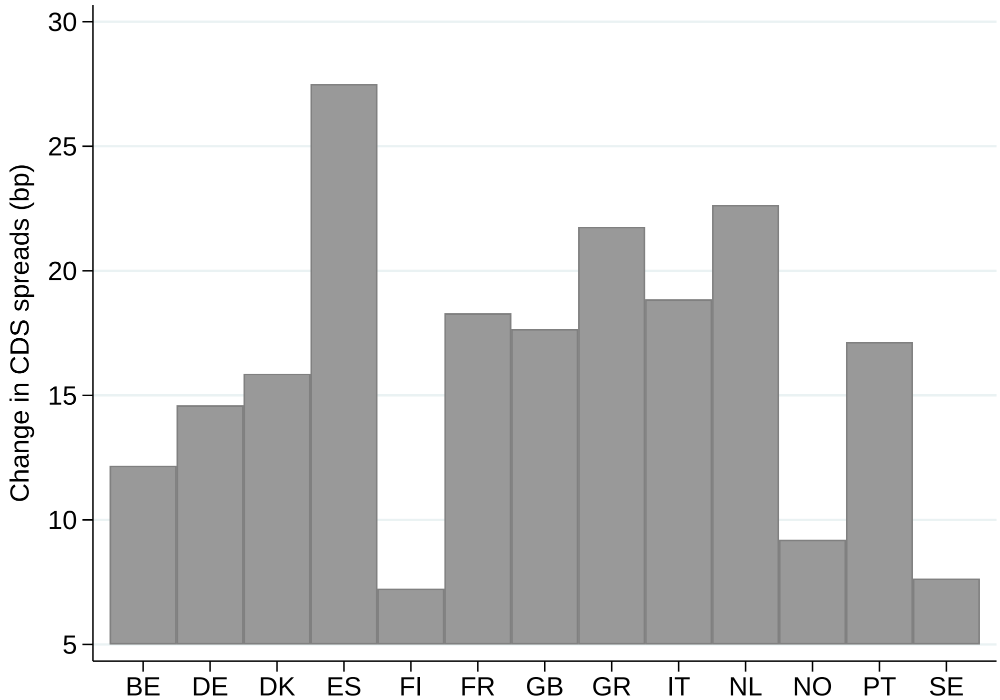
Appendix A. Additional figures and tables

Figure A1: Orbis dataset sample coverage



Notes: This table reports firm coverage in our balanced sample relative Eurostat Structural Business Statistics (SBS). For each country and year in our sample, we calculate total gross output across firms as a share of the equivalent aggregate statistics from Eurostat SBS. Our sample is restricted to firms that report data on employment, gross output, tangible fixed assets, and materials in Orbis, and continuously exist during our sample period (4 years before and after the GFC).

Figure A2: Change in CDS Spreads around the Lehman Brothers collapse



Notes: This figure plots the change in the average 5-year CDS spreads of banks in each country one week before vs. after the Lehman brothers collapse on September 15, 2008. The CDS data comes from the Markit database, expressed in units of basis points.

Table A1: Transition Matrix: Micro/Small/Medium/Large Firms

Transition matrix: Frequency

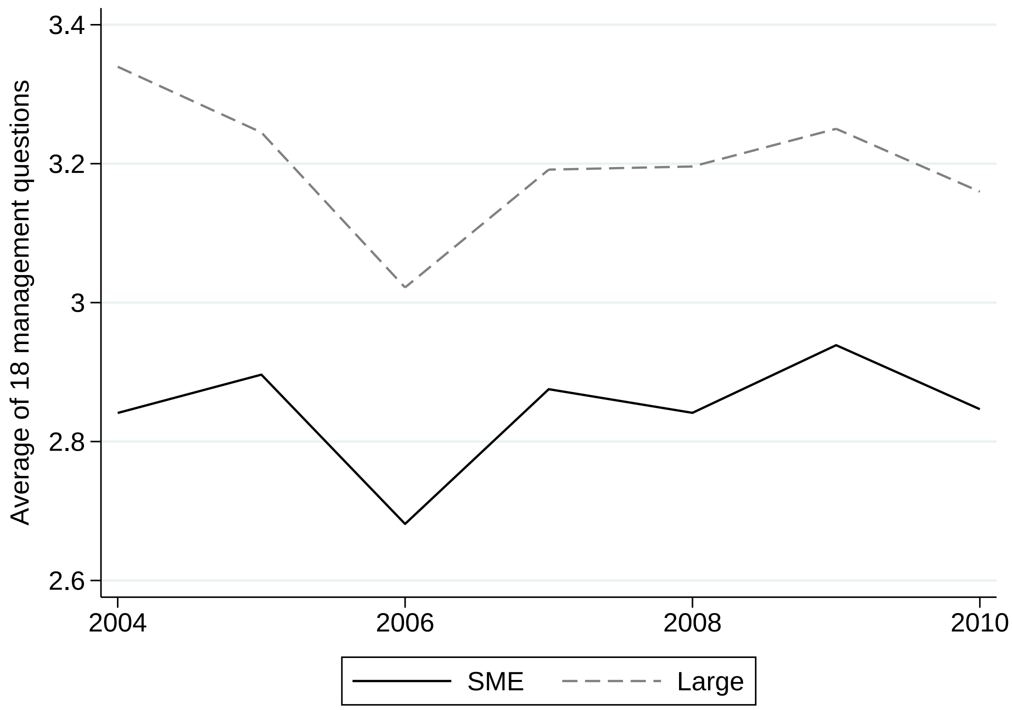
Pre/Post Crisis	Micro	Small	Medium	Large	Total
Micro	343,961	28,574	138	11	372,684
Small	27,875	196,531	12,215	62	236,683
Medium	247	8,289	58,459	3,229	70,224
Large	23	81	2,078	19,840	22,022
Total	372,106	233,475	72,890	23,142	701,613

Transition matrix: Probability

Pre/Post Crisis	Micro	Small	Medium	Large	Total
Micro	92.3%	7.7%	0.0%	0.0%	100.0%
Small	11.8%	83.0%	5.2%	0.0%	100.0%
Medium	0.4%	11.8%	83.2%	4.6%	100.0%
Large	0.1%	0.4%	9.4%	90.1%	100.0%
Total	53.0%	33.3%	10.4%	3.3%	100.0%

Notes: This table shows the frequency (top panel) and probability (bottom panel) of a firm switching between the micro/small/medium/large classification pre (rows) and post (columns) crisis. The calculation is based on the balanced sample of all Orbis firms which report employment from 2004 to 2011. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total.

Figure A3: Trends in management quality



Notes: This figure plots the average *management quality* of SMEs and large firms for each year in our sample. *Management quality* is the average score of 18 key management practices from the World Management Survey as used in Bloom et al. (2014). Each practice is scored on a scale from 1 (worst practice) to 5 (best practice). The survey covers Germany, Spain, France, Great Britain, Greece, Italy, Poland, Portugal, and Switzerland. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total.

Table A2: Management quality

	Management Quality		ΔManagement Quality Gap	
	(1)	(2)	(3)	(4)
Micro	-0.0423***	-0.0418***	-0.0308***	-0.0295***
	(0.0035)	(0.0035)	(0.0055)	(0.0058)
Micro × Management		0.0035		-0.0095
		(0.0030)		(0.0107)
Small	-0.0182***	-0.0181***	-0.0082**	-0.0085**
	(0.0028)	(0.0028)	(0.0039)	(0.0037)
Small × Management		0.0004		0.0034
		(0.0030)		(0.0077)
Medium	-0.0038*	-0.0032	0.0030	0.0022
	(0.0022)	(0.0021)	(0.0031)	(0.0030)
Medium × Management		0.0039		0.0070
		(0.0027)		(0.0078)
Observations	178,473	178,473	70,612	70,612
R^2	0.62	0.62	0.62	0.62
Mean dep var	-0.05	-0.05	-0.06	-0.06
Lag TFP control	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes

Notes: Each dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. *Management quality* is based on the World Management Survey, using the precrisis average score of 18 key management practices as used in Bloom et al. (2014). Each item is scored on a scale from 1 (worst practice) to 5 (best practice). The survey covers manufacturing firms from Germany, Spain, France, Great Britain, Greece, Italy, Poland, Portugal, and Switzerland. The original firm-level survey is aggregated as an average for each country and 2-digit industry groups. Δ*Management Quality Gap* is the postcrise change in the management quality of SMEs vis-à-vis large firms. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A3: Technological leadership and markups

	Leader Firm		Cobb-Douglas Markup		Translog Markup	
	(1)	(2)	(3)	(4)	(5)	(6)
Micro	-0.0584***	-0.0479***	-0.0524***	-0.0455***	-0.0570***	-0.0485***
	(0.0028)	(0.0025)	(0.0024)	(0.0028)	(0.0024)	(0.0028)
Micro $\times$ ΔCDS		-0.0313***		-0.0209***		-0.0224***
		(0.0045)		(0.0050)		(0.0049)
Small	-0.0339***	-0.0284***	-0.0304***	-0.0263***	-0.0338***	-0.0287***
	(0.0022)	(0.0021)	(0.0021)	(0.0025)	(0.0020)	(0.0025)
Small $\times$ ΔCDS		-0.0276***		-0.0203***		-0.0213***
		(0.0035)		(0.0042)		(0.0040)
Medium	-0.0119***	-0.0132***	-0.0147***	-0.0138***	-0.0169***	-0.0155***
	(0.0014)	(0.0017)	(0.0017)	(0.0020)	(0.0016)	(0.0020)
Medium $\times$ ΔCDS		-0.0139***		-0.0110***		-0.0114***
		(0.0025)		(0.0034)		(0.0032)
Observations	667,175	209,175	225,856	82,460	225,856	82,460
R^2	0.61	0.64	0.63	0.64	0.63	0.64
Mean dep var	-0.05	-0.04	-0.04	-0.03	-0.04	-0.03
Lag TFP control	Yes	Yes	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. Columns 1 and 2 control for whether a firm was a leader firm during the precrisis period. A firm is defined as a *leader firm* if its precrisis level of TFP was above the 90th percentile. Columns 3 through 6 control for firm-level markups. *Markups* are estimated using a *Cobb-Douglas* or *translog* production function, following De Loecker and Warzynski (2012) and Diez et al. (2019). We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

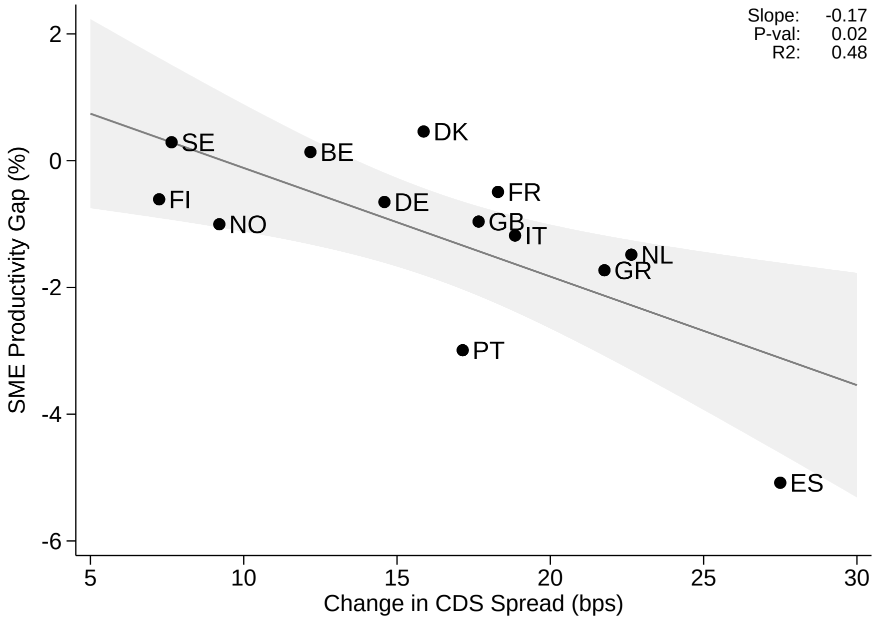
Table A4: Alternative explanations

	High Market Concentration	High TFP Dispersion (Within Industry)	High TFP Dispersion (Across Industries)
	(1)	(2)	(3)
Micro	-0.0555***	-0.0545***	-0.0573***
	(0.0029)	(0.0030)	(0.0041)
Micro × Industry Characteristic	0.0053*	0.0006	0.0051*
	(0.0030)	(0.0028)	(0.0029)
Small	-0.0300***	-0.0287***	-0.0321***
	(0.0024)	(0.0026)	(0.0034)
Small × Industry Characteristic	0.0051*	-0.0003	0.0012
	(0.0028)	(0.0027)	(0.0027)
Medium	-0.0111***	-0.0100***	-0.0142***
	(0.0017)	(0.0019)	(0.0028)
Medium × Industry Characteristic	0.0021	-0.0007	0.0021
	(0.0027)	(0.0025)	(0.0026)
Observations	646,790	646,790	646,790
R^2	0.60	0.60	0.60
Mean dep var	-0.05	-0.05	-0.05
Lag TFP control	Yes	Yes	Yes
Input TFP average	No	No	Yes
Balance sheet controls	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. In column 1, the industry characteristic is *High Market Concentration*, a dummy variable for (4-digit) industry–country groups whose precrisis sales of the top 8 firms as a share of the top 20 firms was above the median. In column 2, the industry characteristic is *High TFP Dispersion (Within Industry)*, a dummy variable for industry–country groups whose precrisis within group dispersion in TFP was above the median. In column 3, the industry characteristic is *High TFP Dispersion (Across Industries)*, a dummy variable equal to one for industry–country groups whose precrisis dispersion in TFP among its suppliers was above the median. The column also controls for the level of supplier's TFP (a dummy variable equal to one for industry–country groups whose precrisis average TFP among its suppliers was above the median). The dispersion and average are weighted using the share of inputs from the OECD Input-Output Tables. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Figure A4: The SME productivity gap and country characteristics

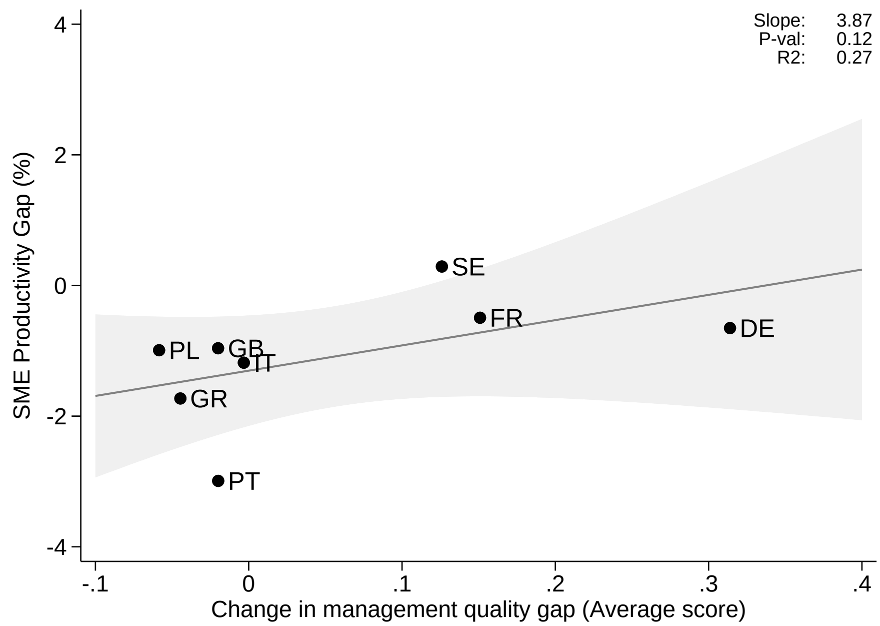
Panel A: Credit



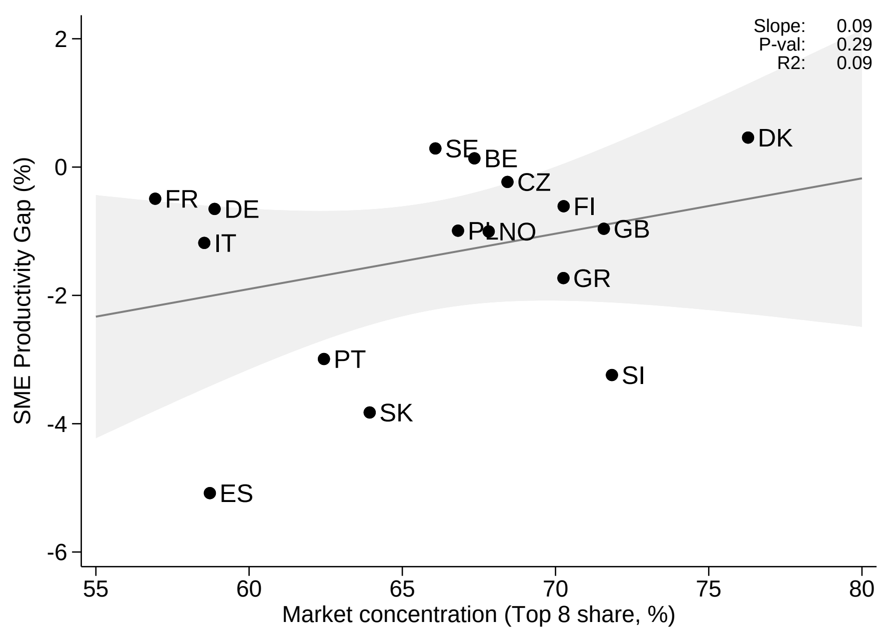
Notes: This figure plots the SME productivity gap against ΔCDS (Country-level). The SME productivity gap is estimated from equation 2 separately for each country. ΔCDS (Country-level) is the change in average 5-year CDS spreads of banks in each country during the week before and after the Lehman Brother collapse. The straight line and shaded area plot the linear fit and 95% confidence interval, respectively. The corresponding slope, p value, and R^2 are reported.

Figure A4: The SME productivity gap and country characteristics (Continued)

Panel B: Management quality



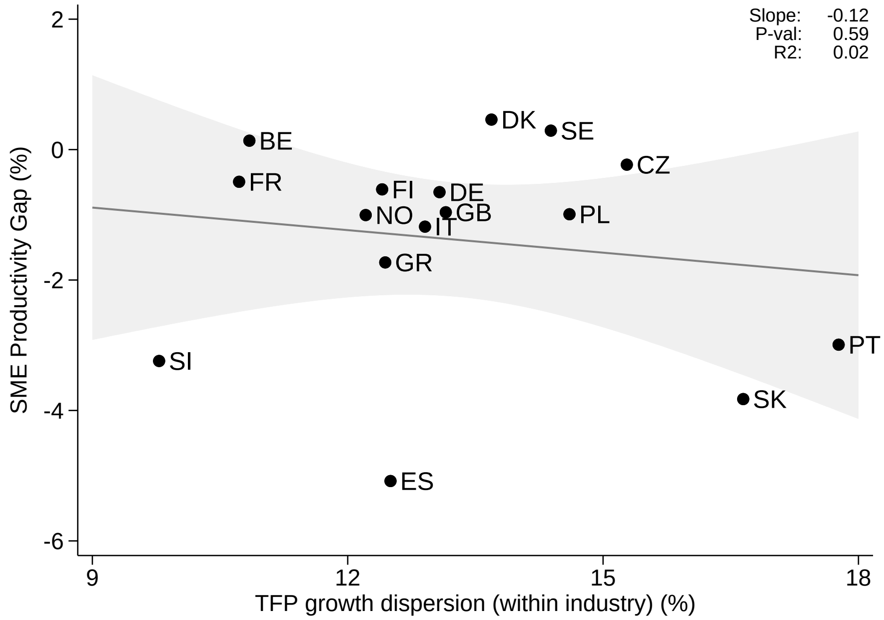
Panel C: Market concentration



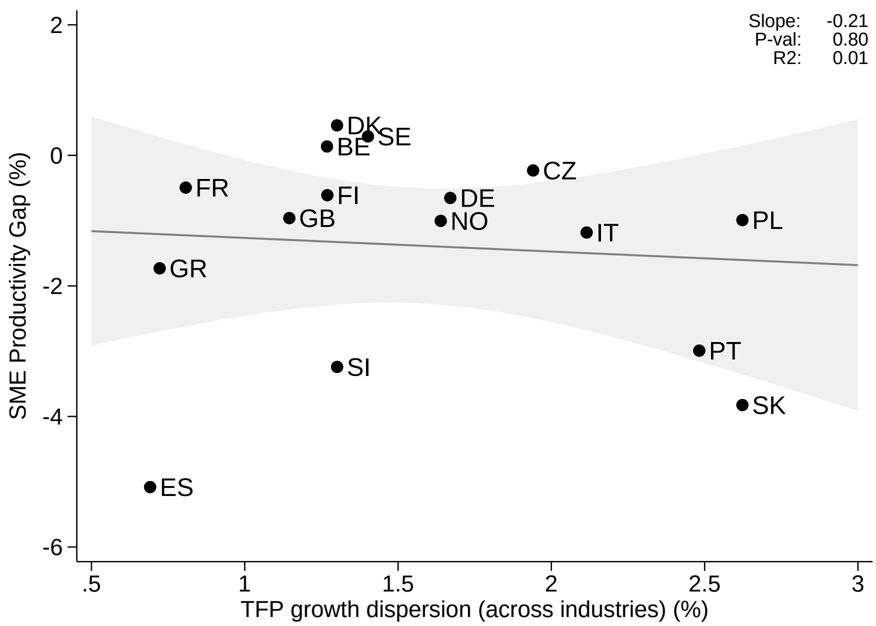
Notes: This figure plots the SME productivity gap against various country-level characteristics. The SME productivity gap is estimated from equation 2 separately for each country. *Change in management quality gap* is the postcrisis change in management quality of SMEs vis-à-vis large firms. *Management quality* is the average score of 18 key management practices among all establishments covered in the World Management Survey. *Market concentration* is calculated at the 4-digit industry × country level as the precrisis sales of the top 8 firms as a share of the top 20 firms. Country-level measures are calculated as industry averages. The straight line and shaded area plot the linear fit and 95% confidence interval, respectively. The corresponding slope, p value, and R^2 are reported.

Figure A4: The SME productivity gap and country characteristics (Continued)

Panel D: Misallocation



Panel E: Productivity bottleneck



Notes: This figure plots the SME productivity gap against various country-level characteristics. The SME productivity gap is estimated from equation 2 separately for each country. *Misallocation* is calculated at the 4-digit industry × country level as the dispersion of the TFP growth of all firms in the industry in the precrisis period. *Productivity bottleneck* is measured by the weighted average of the TFP growth dispersion of each industry's suppliers. The weights are the share of inputs from the OECD Input-Output Tables. Country-level measures are calculated as industry averages. The straight line and shaded area plot the linear fit and 95% confidence interval, respectively. The corresponding slope, p value, and R^2 are reported.

Table A5: Decomposition of the SME productivity gap

	SME Productivity gap	L gap	K gap	IK gap	Estimation adjustment in L	Estimation adjustment in K
Conventional (Solow) model (% of VA gap)	13.3%	59.9%	26.8%			
Solow with estimation adjustment (% of VA gap)	13.3%	59.0%	25.4%	0.4%	0.9%	1.4%
Intangible-augmented model (% of VA gap)	15.2%	59.0%	25.4%	0.4%		
IK contribution in intangible-augmented model	2.7%					
% of SME productivity gap in conventional model explained by IK (IK gap plus estimation adjustment in L and K)	**20.5%**					

Notes: This table decomposes output and input growth for SMEs and large firms under two forms of production functions. SME productivity gap defined as $\Delta TFPgrowth_{Large} - \Delta TFPgrowth_{SME}$. It is calculated by first taking the difference in average TFP growth between the pre- and postcrisis periods for large firms and SMEs, respectively, then taking their differences. SME labor gap (L gap), physical capital gap (K gap), and intangible capital gap (IK gap) are similarly defined. The conventional model estimates equation 1. The model including intangibles estimates $y_{it} = a_{it} + \beta_j^k k_{it} + \beta_j^{ik} ik_{it} + \beta_j^l l_{it}$, where ik_{it} is the log of real intangible capital stock. The estimation is performed in the balanced sample of all firms which report y_{it}, l_{it}, k_{it}, and ik_{it} from 2004 to 2011.

Table A6: Credit market vulnerability: Robustness

	Strength of Top Bank		Credit Condition	
	(1) Bank capital	(2) CDS presence	(3) ΔNet Percentage	(4) ΔDiffusion Index
Micro	-0.0811***	-0.0659***	-0.0844***	-0.0837***
	(0.0075)	(0.0041)	(0.0050)	(0.0050)
Micro × Credit	0.0304**	0.0163***	-0.1551***	-0.2359***
	(0.0135)	(0.0048)	(0.0202)	(0.0315)
Small	-0.0542***	-0.0418***	-0.0580***	-0.0573***
	(0.0062)	(0.0031)	(0.0038)	(0.0038)
Small × Credit	0.0275***	0.0178***	-0.1396***	-0.2118***
	(0.0104)	(0.0038)	(0.0162)	(0.0251)
Medium	-0.0237***	-0.0191***	-0.0301***	-0.0291***
	(0.0052)	(0.0024)	(0.0031)	(0.0031)
Medium × Credit	0.0013	0.0069**	-0.0943***	-0.1405***
	(0.0086)	(0.0032)	(0.0134)	(0.0205)
Observations	28,593	221,096	196,158	196,158
R^2	0.61	0.63	0.63	0.63
Mean dep var	-0.06	-0.05	-0.04	-0.04
Lag TFP control	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. Each column uses different measures of *Credit* as indicated in the column header. In columns 1 and 2, we measure creditor strength using the *top bank* (the first bank for each firm in AMADEUS's Banker variable). *Bank capital* is a dummy variable equal to one if the average precrisis regulatory Tier 1 capital (in percentage of Risk-Weighted Assets) of a firm's creditor banks is above the median. *CDS presence* is a dummy variable equal to one if a firm's creditor bank was present in the CDS market prior to the Lehman Brother collapse. Net percentage is the difference between the share of banks in the Euro area Bank Lending Survey (BLS) reporting that credit standards applied to loan approvals have been tightened versus eased. Diffusion index is the weighted difference of the same survey, where lenders who have answered "considerably" are given a weight twice as high as lenders who answered "somewhat." ΔNet Percentage and ΔDiffusion index denote changes in the respective measures from 2008 Q3 to 2008 Q4. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A7: Southern Europe

	(1) Full Sample	(2) Private	(3) Manufacturing	(4) Non-manufacturing
Micro	-0.0334***	-0.0331***	-0.0237***	-0.0357***
	(0.0025)	(0.0025)	(0.0041)	(0.0028)
Micro × Southern Europe	-0.0470***	-0.0472***	-0.0343***	-0.0541***
	(0.0047)	(0.0047)	(0.0058)	(0.0059)
Small	-0.0162***	-0.0159***	-0.0072**	-0.0184***
	(0.0019)	(0.0019)	(0.0033)	(0.0022)
Small × Southern Europe	-0.0340***	-0.0341***	-0.0225***	-0.0406***
	(0.0040)	(0.0040)	(0.0052)	(0.0050)
Medium	-0.0057***	-0.0054***	0.0005	-0.0076***
	(0.0015)	(0.0015)	(0.0026)	(0.0018)
Medium × Southern Europe	-0.0196***	-0.0197***	-0.0107**	-0.0251***
	(0.0030)	(0.0031)	(0.0045)	(0.0037)
Observations	667,175	666,389	137,947	529,228
R^2	0.61	0.61	0.62	0.61
Mean dep var	-0.05	-0.05	-0.06	-0.05
Lag TFP control	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.00	0.00	0.00	0.00
Small = Medium (p-val)	0.00	0.00	0.00	0.00

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. *Southern Europe* is a dummy variable equal to one if the firm is located in Spain, Greece, Italy, or Portugal. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A8: SME productivity gap: Excluding one country at a time

	(1) Ex. BE	(2) Ex. CZ	(3) Ex. DE	(4) Ex. DK	(5) Ex. EE	(6) Ex. ES	(7) Ex. FI	(8) Ex. FR	(9) Ex. GB
Micro	-0.0551***	-0.0551***	-0.0544***	-0.0540***	-0.0531***	-0.0428***	-0.0551***	-0.0596***	-0.0545***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0023)	(0.0028)	(0.0034)	(0.0027)
Small	-0.0296***	-0.0297***	-0.0294***	-0.0286***	-0.0279***	-0.0198***	-0.0294***	-0.0327***	-0.0292***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0017)	(0.0021)	(0.0026)	(0.0021)
Medium	-0.0108***	-0.0110***	-0.0113***	-0.0104***	-0.0100***	-0.0062***	-0.0109***	-0.0130***	-0.0106***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0017)	(0.0014)
Observations	658,740	653,123	664,903	665,306	658,120	460,492	642,328	506,140	659,462
R^2	0.61	0.61	0.61	0.61	0.61	0.62	0.61	0.60	0.61
Mean dep var	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.07	-0.05
Lag TFP control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Small = Medium (p-val)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	(1) Ex. GR	(2) Ex. IT	(3) Ex. NL	(4) Ex. NO	(5) Ex. PL	(6) Ex. PT	(7) Ex. SE	(8) Ex. SI	(9) Ex. SK
Micro	-0.0543***	-0.0513***	-0.0541***	-0.0545***	-0.0539***	-0.0537***	-0.0587***	-0.0541***	-0.0537***
	(0.0027)	(0.0031)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Small	-0.0290***	-0.0283***	-0.0288***	-0.0288***	-0.0285***	-0.0284***	-0.0319***	-0.0287***	-0.0284***
	(0.0021)	(0.0024)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0022)	(0.0021)	(0.0021)
Medium	-0.0104***	-0.0114***	-0.0105***	-0.0101***	-0.0102***	-0.0102***	-0.0124***	-0.0104***	-0.0104***
	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Observations	661,477	541,239	667,063	654,383	662,985	663,772	595,356	661,310	665,776
R^2	0.61	0.61	0.61	0.61	0.61	0.60	0.61	0.61	0.61
Mean dep var	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
Lag TFP control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Small = Medium (p-val)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A9: SME productivity gap: All countries weighted equally

	(1) Full Sample	(2) Private	(3) Manufacturing	(4) Non-manufacturing
Micro	-0.0543***	-0.0542***	-0.0418***	-0.0570***
	(0.0066)	(0.0066)	(0.0069)	(0.0080)
Small	-0.0320***	-0.0317***	-0.0190***	-0.0346***
	(0.0055)	(0.0056)	(0.0054)	(0.0069)
Medium	-0.0151***	-0.0148***	-0.0061	-0.0172***
	(0.0044)	(0.0045)	(0.0038)	(0.0056)
Observations	667,175	666,389	137,947	529,228
R^2	0.67	0.67	0.71	0.66
Mean dep var	-0.05	-0.05	-0.06	-0.05
Lag TFP control	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.00	0.00	0.00	0.00
Small = Medium (p-val)	0.00	0.00	0.00	0.00

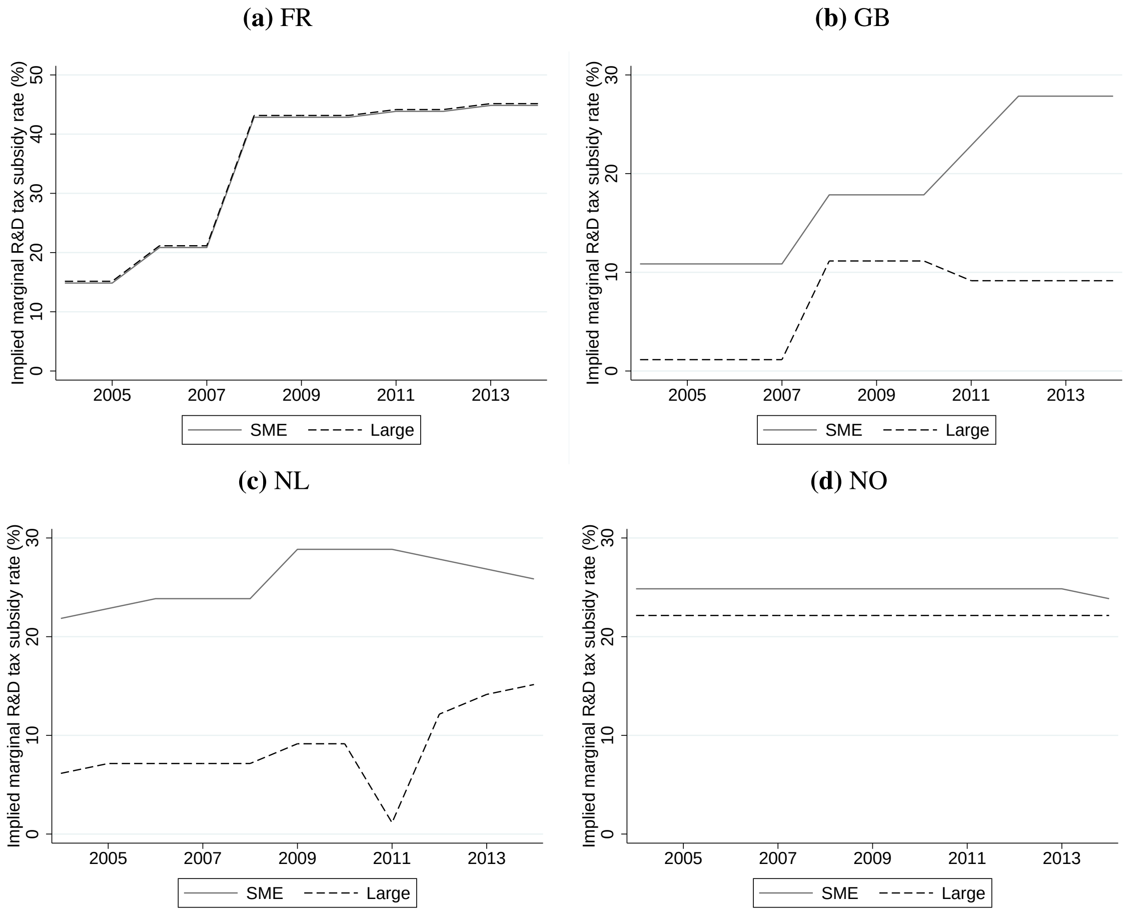
Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. Observations in the regression weighted by the inverse of the number of firms in each country. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A10: Sample

	(1) Clean Sample 6 Countries	(2) Post-crisis As 2008-2009	(3) Post-crisis As 2010-2012	(4) Allow Entry And Exit
Micro	-0.0607***	-0.0758***	-0.0357***	-0.0685***
	(0.0036)	(0.0037)	(0.0027)	(0.0043)
Small	-0.0350***	-0.0438***	-0.0183***	-0.0369***
	(0.0029)	(0.0027)	(0.0023)	(0.0035)
Medium	-0.0135***	-0.0182***	-0.0075***	-0.0178***
	(0.0020)	(0.0021)	(0.0019)	(0.0025)
Observations	379,684	780,394	599,719	940,591
R^2	0.60	0.42	0.41	0.40
Mean dep var	-0.04	-0.09	-0.04	-0.07
Lag TFP control	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes
Micro = Small (p-val)	0.00	0.00	0.00	0.00
Small = Medium (p-val)	0.00	0.00	0.00	0.00

Notes: The dependent variable is the difference in the average TFP growth between the pre- and postcrisis periods. The *Clean Sample* restricts the sample to 6 European countries with stable coverage of firms in Orbis (Denmark, France, Germany, Netherlands, Spain, and the United Kingdom). Column 2 defines the postcrisis period as the two years immediately after the GFC (2008-2009). Column 3 defines the postcrisis period around the European sovereign debt crisis (2010-2012). Column 4 uses the full unbalanced panel of firms, allowing firm entry and exit. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Figure A5: Implied marginal R&D tax subsidy rates



Notes: This figure plots the marginal R&D tax subsidy rates implied by the B-index from OECD (2021). The B-index measures the pre-tax income needed for a "representative" firm to break even on a marginal monetary unit of R&D outlay. The implied subsidy rate is estimated for four firm profiles depending on whether the firm is profitable or large.

Table A11: R&D Tax Subsidy

	Δ Intangible Share		Δ Patent Applications	
	(1)	(2)	(3)	(4)
Micro	-0.0382***	-0.0382***	-0.2879***	-0.2911***
	(0.0090)	(0.0093)	(0.0753)	(0.0773)
Micro $\times$ ΔR&D Tax Subsidy Gap		-0.0007		-0.0470
		(0.0044)		(0.0292)
Small	-0.0291***	-0.0292***	-0.2218***	-0.2315***
	(0.0081)	(0.0084)	(0.0568)	(0.0601)
Small $\times$ ΔR&D Tax Subsidy Gap		-0.0055		0.0200
		(0.0036)		(0.0262)
Medium	-0.0255***	-0.0258***	-0.2002***	-0.2195***
	(0.0070)	(0.0074)	(0.0502)	(0.0561)
Medium $\times$ ΔR&D Tax Subsidy Gap		-0.0033		0.0302
		(0.0031)		(0.0213)
Observations	666,043	666,043	4,824	4,824
R^2	0.52	0.52	0.47	0.47
Mean dep var	-0.028	-0.028	0.047	0.047
Lag dep var	Yes	Yes	Yes	Yes
Balance sheet controls	Yes	Yes	Yes	Yes
Industry $\times$ Country FEs	Yes	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average between the pre- and postcrisis periods. *Intangible share* is the firm's intangible investment as a share of total investment. *Patent applications* is firm's number of patent applications from the Worldwide Patent Statistical Database (PATSTAT). Δ *R&D Tax Subsidy gap* is the gap in the postcrisis change in the marginal R&D tax subsidy rates applied to SMEs vis-à-vis large firms. The tax subsidy rate is based on the B-index from OECD (2021). The B-index measures the pre-tax income needed for a "representative" firm to break even on a marginal monetary unit of R&D outlay. We apply the EU definition in designating micro, small, and medium-sized firms based on precrisis employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry $\times$ country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

Table A12: Employment and gross output share by firm size groups

	Employment (% of total)				
	Large	SME	SME: Micro	SME: Small	SME: Medium-sized
18-country sample (Eurostat)	34.3	65.7	28.1	19.1	18.5
All EU (Eurostat)	34.2	65.8	27.8	19.1	18.9
	Gross output (% of total)				
	Large	SME	SME: Micro	SME: Small	SME: Medium-sized
18-country sample (Eurostat)	48.7	51.3	17.8	14.6	18.9
All EU (Eurostat)	46.7	53.3	14.8	17.7	20.9

Notes: This table shows the share of employment (top panel) and gross output (bottom panel) for each firm size group from Eurostat Structural Business Statistics (SBS). The calculation for the *18-country* sample is based on the 18 countries studied in the paper. The calculation for the *All EU* sample is based on aggregated statistics for all EU countries covered in Eurostat. We follow the Eurostat definition in designating micro, small, and medium-sized enterprises as firms that have employees below certain thresholds.

Table A13: Recession in 2000

	(1)	(2)	(3)	(4)
Micro	-0.0304	-0.0033	-0.0294	-0.0037
	(0.0340)	(0.0366)	(0.0373)	(0.0376)
Micro × Bank strength			-0.0997	0.0147
			(0.1197)	(0.0877)
Small	-0.0031	-0.0039	-0.0089	-0.0037
	(0.0337)	(0.0338)	(0.0366)	(0.0353)
Small × Bank strength			0.1002	0.0496
			(0.0820)	(0.0793)
Medium	0.0085	-0.0163	0.0030	-0.0128
	(0.0360)	(0.0260)	(0.0422)	(0.0302)
Medium × Bank strength			0.0291	-0.0162
			(0.0575)	(0.0457)
Observations	822	822	822	822
R^2	0.36	0.82	0.36	0.82
Lag TFP control	No	Yes	No	Yes
Balance sheet controls	No	Yes	No	Yes
Industry × Country FEs	Yes	Yes	Yes	Yes

Notes: The dependent variable is the difference in the average TFP growth between the 4-year pre and post period of the 2000 recession. *Bank strength* is a dummy variable equal to one if the average precrisis regulatory Tier 1 capital (in percentage of Risk-Weighted Assets) of a firm's creditor banks is above the median. We apply the EU definition in designating micro, small, and medium-sized firms based on pre-2000 employment, annual turnover, and balance sheet total. Standard errors (in parentheses) are clustered at the four digit industry × country level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent, respectively.

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