In the Right Hands?
Capital Inflows and Allocation of Credit Across Firms: Evidence from Emerging Europe

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JOB MARKET PAPER

November, 2022

Abstract

We study how, and through which channels, international capital inflows influence the domestic allocation of credit within industries, across firms that differ in their ex-ante productivity. Using a large panel of firms from 12 Central Eastern European countries over 2003–2017, we find that higher debt inflows increase the credit growth rates of low TFP firms significantly more than their more productive industry peers. These differentials materialize through the intensive and extensive margins of credit, for both non-resident inflows and outflows, and occur mostly when foreign capital is driven by global supply factors. A different sample of more advanced countries yield significantly smaller differential effects that are limited to episodes of foreign disinvestment. Banks directed foreign funds more towards low TFP firms because these firms are relatively riskier and have more collateral. This suggests a risk-taking channel of capital inflows that leads to a misallocation of credit towards the less productive.

JEL codes: F30, F41, F43, G15

Keywords: Capital Inflows, Credit Allocation, Productivity, Emerging Countries

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‡I am extremely grateful to my PhD supervisor, Cédric Tille, for insightful remarks and his continuous guidance and support. This paper has greatly benefited from numerous discussions with Rahul Mukherjee. I am indebted to Christian Proebsting for kindly providing access to some of the data used in this paper. I also appreciate helpful comments from Ugo Panizza, Michele Pellizzari, Beatrice Weder di Mauro, Steven Wei Ho, Sehkhar Hari Kumar, Yannick Timmer, Cian Ruane, and seminar participants at the Graduate Institute and the University of Geneva. All errors and omissions are my own.

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1. Introduction

The relationship between capital inflows and economic growth is not clear cut, and can even turn negative, especially in the long run.[1] For emerging and more advanced recipient economies, the question arises as to how the flows of foreign capital—especially in debt—are intermediated, and whether the financial system ‘‘pipes’’ channel them towards the productive part of the economy. Besides higher capital accumulation, long-term growth depends crucially on the ability to direct resources to high-productivity firms, enabling them to invest and upscale (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). In this regard, the efficiency of bank credit allocation holds important implications, and a large literature highlights the role of financial frictions in driving capital misallocation across firms/sectors.[2] International financial flows, through their effects on the supply and price of loanable funds, affect local banks' lending which, in turn, pose a risk that they might be misallocated, especially if driven by global supply factors and channeled through a financial sector beset by inefficiencies.

The nexus between capital inflows, credit allocation and aggregate productivity has received a growing attention in the literature, with some studies reporting adverse effects of these inflows on resource allocation across sectors (e.g. Reis, 2013; Benigno et al., 2015), others a distorted allocation of credit within sectors towards low productive firms (e.g. Gopinath et al., 2017; Barbosa et al., 2020), but still remains a matter of debate with also some evidence of improved allocation (e.g. Larrain and Stumpner, 2017; Cingano and Hassan, 2020).

Against this background, we explore empirically whether capital inflows affect differentially the credit growth of ex-ante low productive firms relative to their more productive industry peers. We bring this question to the context of emerging economies, which, to our knowledge, has received empirically limited attention. Our study concentrates on a sample of firms from 12 emerging countries in Central and Eastern Europe (CEE) over 2003–2017. These ‘‘transition’’ economies experienced a full boom-bust economic cycle over the period of analysis, led by large episodes of capital inflows and rapid credit growth as well as severe liquidity shocks arising from departure of foreign capital. The stronger the financial frictions emerging markets are subject to, combined with the large developments CEE experienced prompt a natural point of departure to our analysis on the banking sector's absorption

[1] BIS (2021) provides a recent review on the new landscape, benefits, and risks of capital flows.

[2] See, among others, Mendoza (2010), Buera et al. (2011), Midrigan and Xu (2014), Moll (2014), Reis (2013), Gopinath et al. (2017), and Asriyan et al. (2021).

capacity at times of capital flows and its ability to channel credit to its most productive use.

For our analysis, we rely on a comprehensive firm-level panel from the ORBIS dataset by the Bureau van Dijk (BvD), focusing on emerging European countries with relatively better coverage. We intensively clean the raw data and merge it with our country-level private gross capital inflow measures. The resulting dataset covers more than 222,000 firms operating in manufacturing and services sectors, and allows us to analyze the effect of capital inflows on the allocation of credit across small and private firms, as small and medium-sized enterprises (SMEs) represent around 90% of firms in our sample.

Our baseline specification with firm fixed effects regresses the firms' flow of credit on a country-specific capital flow variable interacted with a firm-level productivity dummy. This enables us to identify how the within-firm effect of capital inflows on firm's debt growth differs across firms of different total factor productivity (TFP), and from the way we define the productivity dummy, to investigate in particular whether higher capital inflows lead to increased credit growth of ex-ante low TFP relative to high TFP firms within the same industry-country-year and size class. Crucially, the inclusion of firm controls with firm, industry-year, country-year and country-industry fixed effects help to control for unobserved time-varying aggregate and local demand conditions and partly tease out the identification of supply-driven effects induced by capital inflows (Acharya et al., 2019; Nanda and Nicholas, 2014; Yesiltas, 2015; Barbiero et al., 2020; Ongena et al., 2016; Degryse et al., 2019).[3]

Our main results are as follows. We find that private debt inflows lead on average to higher credit growth for all types of firms, whether small or large, or whether firms are categorized as ex-ante low or high TFP firms. While small firms show a higher sensitivity as expected, interestingly however, credit along the intensive margin tends to go relatively more towards the least productive firms. The differential effect is statistically significant and economically large, especially within SMEs and when the comparison focuses on the tails of the TFP distribution within industries. For instance, in a country experiencing a 5

[3] A bank-firm loan-level dataset would provide greater granularity and a more rigorous identification by including a full set of firm-year dummies to control for any shocks to firm-specific credit demand. This strategy requires privileged access to credit registry data, that often lack in our sample of countries. Besides, loan-level studies focus often on a single country—a recent exception is Altavilla et al. (2020), which combines 15 European credit registers (with 3 countries from our sample) in the context of the ECB's AnaCredit project. Moreover, the inclusion of firm-year fixed effects restricts the sample to firms that borrow concurrently from multiple banks in a given year. This might introduce sample selection effect (Degryse et al., 2019), especially among SMEs and for emerging markets where the share of multiple-bank borrowers is usually low—e.g. 10% in Slovakia, 15% in Czech Republic and 29% in Romania (Altavilla et al., 2020), while 50% in Spain (Jiménez et al., 2020).

percentage points cumulative increase in debt inflows (equivalent to one standard deviation), the log-difference in financial debt between an average SME firm in the lowest quartile and one in the upper quartile of the TFP distribution within the same industry is -2.43 percentage points. These intensive margin effects are complemented by extensive margin effects, too.[4] Results indicate that within SMEs, low TFP firms tend to enjoy after capital inflows both a larger probability to access credit markets as well as a larger committed credit at entry.

It is, nonetheless, possible that this additional credit enable them to sustain unmet investment needs in productivity-enhancing activities, and eventually lead to a catch-up. However, we find no evidence that initially low TFP firms show on average a higher within-firm sensitivity of future TFP growth to the use of external finance, but rather the opposite. The confluence of results for our sample of emerging countries lends support to the view that capital inflows tend to induce a ‘‘misallocation’’ of credit towards the least productive firms within an industry. Extending relatively more credit to these firms means less funding to more productive and inefficiently under-resourced firms that could use these additional funds in a more productive way, or the least could attract more capital and labor inputs to expand.

We conduct an extensive set of robustness checks and show that our results withstand different proxies of firm-level productivity (e.g. markup-adjusted revenue TFP) and settings to identify the most productive firms, alternative ways of measuring firm's debt, and various capital inflow measures constructed from Balance of Payments (BOP) data or cross-border bank positions from the Bank for International Settlements (BIS). We further confirm that our core findings are mostly driven by the changes in push factors of foreign capital flows.

We then investigate why would banks at time of abundant liquidity allocate relatively more credit to these low-productivity firms. We start by exploring the differential effect of capital inflows for other firm characteristics, aside from the productivity dimension. On the assumption that low TFP firms are on average ex-ante more credit constrained, our results could reflect the positive spillover effect of capital inflows in relieving firms' credit constraints. Debt inflows induce however a relatively larger lending towards firms with ex-ante high collateral availability, proxied by firms' fixed assets, which is consistent with Gopinath et al. (2017)'s size-dependent borrowing constraints and with di Giovanni et al. (2021)'s results that debt inflows do not necessarily relax banks' demand for collateral. Broadly in support

[4] We introduce two alternative dependent variables that accommodate adjustments on the extensive margin, with the Davis et al. (1996) mid-point growth rate, or with the first difference of debt scaled by lagged total assets which provides a different perspective on the magnitude of the economic effects.

to an observed-risk hypothesis whereby collateral is associated with riskier borrowers (Berger and Udell, 1990), our results show as well a credit allocation skewed towards the riskier firms, as proxied for instance by the Altman's Z score. Further, we show that credit is not flowing systematically towards low TFP firms, in that there exists some nuances along the firms' collateral and risk heterogeneity. But, conditional on being of high TFP, lending increases the least for low collateral or low risk firms, which deviates from what classic risk-return trade-off would predict. The differential effect of capital inflows between low TFP–high risk firms and high TFP–low risk firms reaches a difference of 5.2 percentage points. Risk considerations from banks pursing higher returns seem to contribute ultimately to our findings, suggesting a risk-taking channel of capital inflows (te Kaat, 2021; Bedayo et al., 2020; Cantú et al., 2022).

The impact on the allocation of credit is not limited to capital inflows surges, but extends to episodes of negative capital inflows. Low productivity firms face in general a milder reduction in credit when non-residents liquidate their holdings. Whilst the direction of the differential effects is symmetric and statistically significant for both types of episodes, the effects of negative capital inflows are larger and occur somewhat faster, although the differentials lessen at longer lags as low TFP firms become eventually less shielded from the contraction of credit supply. These results for negative capital inflows could be symptomatic of evergreening or zombie lending (e.g. Schivardi et al., 2021), and/or reflect increasing bank risk-taking at times of accommodative policies during outflows episodes (Bittner et al., 2022).

Finally, after re-weighting the data to mitigate concerns of sample representativeness across- and within-countries, we contrast our estimates on emerging Europe from a sample of 10 advanced European economies. In this latter sample, foreign capital is also associated with a higher flow of credit to low TFP firms, yet the differentials are significantly smaller, consistent with the view that distortions in emerging markets have greater bite. Further, the effects are much more asymmetric; while inflows do not necessarily lead banks in advanced countries to favor more the least productive or more marginal firms, episodes of foreign disinvestment still induce larger corrections in lending among higher TFP firms.

The remainder of this paper is organized as follows. Section 2 presents a review of the literature that our paper contributes to. Section 3 introduces the data, some basic stylized facts, and outlines next our empirical strategy. We present our benchmark results in Section 4, followed by a discussion in Section 5 on the potential explanations behind these. Section 6 provides the results of several extensions and robustness checks. Section 7 concludes.

2. Literature Review

Our paper is related to two main strands of literature. First, it belongs to the growing body of research on the link between credit allocation and aggregate productivity growth. In this literature, recent studies draw a connection between episodes of large capital inflows and slowdown in TFP growth, caused by a misallocation of resources across and within industries.

Analyzing the impact of capital flows on sectoral allocation and aggregate TFP, Reis (2013) for Portugal in the 2000s, and Benigno et al. (2015) for a large cross-country panel, document that large capital inflows, intermediated through domestic banks, can trigger a reallocation of productive resources away from the manufacturing sector—where TFP growth is generally higher—towards non-tradable sectors such as real estate or retail trade. This leads to a decline in TFP growth, a "financial resource curse" consistent with theories by Benigno and Fornaro (2014), Kalantzis (2015), Benigno et al. (2020), and Bleck and Liu (2018)'s predictions for sectors with differences in financial frictions.[5] While these studies look at between-sector misallocation, we use instead firm-level data to investigate the effect of capital inflows on the within-sector allocation of credit across firms of different productivity.

Our paper relates most closely to studies exploring the effect of capital inflows on the allocation of credit (and productive resources) across heterogeneous firms. Dynamic models of financial frictions predict that financial liberalization episodes, by relaxing borrowing constraints, improve overall TFP through a more efficient allocation of resources across firms (Buera et al., 2011; Midrigan and Xu, 2014).[6] These predictions find some empirical support. For instance, Larrain and Stumpner (2017) rely on a sample of manufacturing firms from ORBIS in 10 Eastern European countries (including 7 from our sample); they find that capital account liberalization, through increased access to capital for credit constrained firms, reduces the within-sector dispersion in MRPK across firms (more so in financially dependent sectors), and map this reduction into aggregate TFP gains.[7] As opposed to a financial liberalization

[5] Relatedly, Saffie et al. (2020) find that foreign capital following the financial liberalization in Hungary accelerated the reallocation of resources towards sectors with high expenditure elasticity like services. Samarina and Bezemer (2016) show that credit in countries with larger capital inflows tends to flow away from firms towards households. In a sample of 117 countries, Müller and Verner (2021) show that private credit expansions geared toward the non-tradable and household sectors are usually followed by slowdowns in TFP growth (see also Borio et al., 2016). Miao and Wang (2014) and Pannella (2017) look at the implications of credit-driven bubbles on between-industry misallocation.

[6] In Aoki et al. (2010)'s model, however, in underdeveloped financial systems, financial liberalization may lead to a decline in TFP as capital inflows are misallocated towards unproductive entrepreneurs.

[7] Exploiting the lifting of restrictions on international borrowing in Hungary in 2001 for a sample of

shock, our interest relies more on transition dynamics post-liberalization,[8] and on the effect of de facto openness, most precisely debt (banking) inflows, on the credit distribution across firms in both manufacturing and service sectors. In essence, Aghion et al. (2019) find that productivity is an increasing function of credit when the latter is rationed, but beyond a certain threshold, the relationship becomes inverted due to negative reallocation effects.

Using a large sample of manufacturing firms collected from ORBIS, Gopinath et al. (2017) document that capital inflows in Southern European countries (most notably Spain and Italy) led to a significant decline in TFP relative to its efficient level by increasing the dispersion in MRPK across firms, but do not find such trends in Germany, France, and Norway. For the case of Spain, the authors calibrate a small open economy model with heterogeneous firms and distortions in the market for capital arising from size-dependent borrowing constraints. They show that the drop in real interest rates following the introduction of the Euro led to a misallocation of capital inflows through a bank credit misallocation, which favored debt and capital accumulation by firms with relatively higher net-worth or more collateral (thus with higher borrowing capacity), that are not necessarily the most productive ones.[9] Using a matched bank-firm-employees dataset for Portugal, Barbosa et al. (2020) find that large capital inflows, despite alleviating financing constraints, can also aggravate the allocative efficiency of labor and skills in the presence of credit market frictions, through an allocation of bank loans titled towards the less productive and older firms.[10] García-Santana et al. (2020) argue instead that the deterioration of resource allocation in Spain that was pervasive across

manufacturing firms, Varela (2018) show that the ensuing large non-FDI inflows increased aggregate TFP—mostly via increase in within-firm productivity—by improving financing terms and encouraging previously policy-discriminated firms to invest more in technology. Bau and Matray (2020) study the effects of the staggered FDI liberalization across Indian industries and find a reduction in capital misallocation between firms, especially in areas with less developed local banking sectors.

[8]In our sample, most foreign capital liberalization episodes took place before 2003 (according to Chinn Ito and Jahan Wang index measures). While such shocks makes a cleaner identification, we privilege external validity and focus on post-2003 years with relatively better coverage in ORBIS.

[9]Apart from an increase in the availability of cheap foreign funds, other studies analyze the impact of lower interest rates on capital misallocation among firms facing financial frictions. Asriyan et al. (2021) develop a general equilibrium model in which declining interest rates may foster investment by the wrong mix of firms, as some low productive firms take advantage of cheaper credit and crowd out investment by more productive financially-constrained firms. Caggese and Pérez-Orive (2022) show that declining interest rates disadvantage credit-constrained expanding productive firms relying more on intangible capital. In Tang (2018), asset price bubbles subsidize the entry decision of the least productive firms. As regards the effect of a credit crunch, Linarello et al. (2019) find among Italian firms a reduction in per-firm productivity, but a positive reallocation of labor shares from less to more productive units in industries or provinces which experienced tighter credit conditions.

[10]Relying on Portuguese credit registry data, Azevedo et al. (2021) show that banks extended credit disproportionately to low productive firms within each sector.

all sectors appear to be the result of government regulation, and not financial frictions.[11]

Some studies have documented the negative productivity effects that arise when banking systems facilitate the survival of so-called "zombie firms", who crowd out borrowing and hog capital and labor at the expense of healthier firms.[12] Our results show that banks appear to reduce their supply of credit more strongly for high productive firms when foreign capital dries up. In that regard, our paper speaks to this literature on zombie lending or evergreening as zombie firms are often defined also in terms of (a lack of) productivity.

The paper closest in spirit to ours is by Cingano and Hassan (2020) which represents one of the few attempts to assess directly the causal effects of foreign capital on the allocation of credit across firms conditional on their ex-ante productivity. Taking advantage of loan-level data for Italy, they show interestingly that the early 2000s boom of inflows did not lead to higher misallocation, as banks relying more on foreign funding disproportionally allocated credit towards firms with ex-ante more collateral but with initially above-average TFP. Like Cingano and Hassan, our paper departs from this literature by analyzing directly the bank lending channel and which type of firms benefited the most from these debt inflows. We provide an in-depth analysis on how credit is allocated, not only across small and large firms, but also within SMEs, focusing on services in addition to manufacturing, and on both the intensive and extensive margins of lending. We also differentiate times of positive gross inflows from episodes of foreign disinvestment, investigate the reasons why such allocation occurs, and highlight some contrast with a sample of more advanced banking sectors, where on average low TFP firms are not granted relatively more credit at times of positive inflows. Admittedly due to data limitations, our identification of the credit supply effects induced by capital inflows is weaker than in their analysis.[13] Still, our sample goes beyond multiple-bank firms and extends the analysis to a cross-country setting, increasing the external validity of our results. Our work also complements theirs and the related literature by exploring these issues in the context of small and open emerging market countries, where domestic bank intermediation of capital inflows is pervasive and credit distortions more acute.[14]

[11]Some papers like Doerr (2020) and Basco et al. (2021) focus on the collateral channel and consider the effect of rising house prices in reallocating credit towards unproductive real estate holding firms.

[12]See e.g., Caballero et al. (2008), Adalet McGowan et al. (2018), and Andrews and Petroulakis (2019) for Japan, OECD, and Europe, respectively. Schivardi et al. (2021) and Acharya et al. (2019) show that credit was not reallocated away from zombie firms during the Eurozone financial crisis.

[13]Ours builds on the assumption that all firms in the same 4-digit sector face a similar credit demand, while theirs is able to relate banks to firms and distinguish neatly between supply and demand effects.

[14]Capital inflows or faster capital accumulation can aggravate allocative efficiency especially if domestic

The literature largely points to the role of credit market frictions, such as collateral constraints (e.g. Reis, 2013; Gopinath et al., 2017; Lanteri and Rampini, 2021), in explaining how capital inflows can amplify the distortions in the allocation of credit and productive factors across firms and sectors. Consistent with the existence of size-dependent borrowing constraints and di Giovanni et al. (2021)'s results that debt inflows do not necessarily relax banks' demand for collateral, we find that firms with ex-ante more tangible assets have a greater sensitivity of credit growth to capital inflows. But the story does not end there. As reflected in the empirical literature on collateral that finds riskier firms to pledge collateral more often (e.g. Berger and Udell, 1990, 1995; Jiménez et al., 2006)—and thus supporting an observed-risk hypothesis—our results suggest that risk considerations from banks pursuing higher returns contribute ultimately to our findings. Capital inflows seem to induce banks to expand relatively more their lending to low TFP firms, as these firms are relatively riskier.

We thus provide further evidence to the nascent empirical studies on the effect of capital inflows on the riskiness of bank credit allocation, namely the risk-taking channel of capital inflows. In this recent literature, Karolyi et al. (2018) and Dinger and te Kaat (2020) rely on bank-level data to analyze the effects of capital flows on bank asset quality. Based on credit registry data for five countries in Latin America, preliminary findings in Cantú et al. (2022) show that banking inflows can lead to an increase in credit to the riskiest firms, especially for banks most dependent on wholesale funding and those with high level of NPLs. Using firm-level data, te Kaat (2021) finds that capital inflows tend to be associated with relatively more credit volumes to the least profitable and riskiest firms, especially in banking sectors more subject to agency problems.[15] Our results fit naturally with the theoretical insights on the link between the rise in loanable funds and interest rate reductions, which are often associated with capital inflows (Baskaya et al., 2017; di Giovanni et al., 2021), and incentives for banks to search for yield as an optimal response to more intense competition and lower margins, among other reasons (Keeton, 1999; Dell'Ariccia and Marquez, 2006; Acharya and Naqvi, 2012; Martinez-Miera and Repullo, 2017; Coimbra and Rey, 2021; Bolton et al., 2021).

financial development is low and credit market frictions more severe, as shown theoretically by Aoki et al. (2010), and empirically across industries by Marconi and Upper (2017).

[15] Our work bears some resemblance with te Kaat's empirical strategy, but differs in two main ways. He focuses on firms with heterogenous profitability where the evidence is drawn from within-firm dynamics that is generalized to a broader comparison between firms, while we explore differentials between ex-ante low-versus high-TFP firms within the same sector-country-year and size class. Secondly, we rely on a sample of SMEs from 12 emerging countries, while his from Worldscope covers 11 advanced countries with 1942 firms (most are publicly quoted, and from France and Germany).

Broadly speaking, our collective findings suggest a bridge between these two recent strands of research on the effects of capital inflows, that both identify banks' credit allocation across firms as the linchpin or the main mediating channel. The literature studying the impact of capital inflows on the misallocation of resources do map financial frictions to misallocation, but hardly consider the financial sector risk-taking as a transmission channel. Regarding the literature on the risk-taking channel of capital inflows, a risky allocation of credit may not only cause concerns about financial stability, but may also bear some unintended consequences in driving credit towards the non-productive part of the economy.

3. Data and Methodology

3.1 Data and Sample Construction

Our firm-level data is obtained from the Bureau van Dijk (BvD)'s ORBIS dataset, and its European subset AMADEUS, which reports harmonized financial accounting information on millions of European firms. Most are private and small firms, as opposed to other micro data sets, such as Compustat and Worldscope, that mainly cover large listed companies. SMEs[16] are heavily reliant on bank lending and generally show a greater sensitivity to external financing conditions, which makes this data set well suited for studying the impact of capital inflows on domestic lending. Besides, unlike census type data, ORBIS has exhaustive information on firms' financial and productive activities from which we can construct measures such as a firm's financial debt exposure and its TFP. Yet, despite the large number of firms included, not all information are available uniformly, especially for emerging countries.

We focus on 12 CEE countries, namely Bosnia-Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Poland, Romania, Serbia, Slovenia, Slovakia, and Ukraine.[17] We disregard other emerging Europe economies for which our variables of interest are only

[16] Based on the European Commission, an SME has less than 250 employees *and* either revenues not exceeding €50 million *or* total assets less than €43 million. We adopt the threshold on employment, but because the annual revenue/asset criteria are high for emerging countries standards, we resort instead on those used by the World Bank. We consider these 3 criteria separately to retain more observations. Hence, unless otherwise specified, we define *SMEs* as firms with less than 250 employees *or* a maximum turnover of \$15 million *or* total assets less than \$15 million. Within SMEs, *micro* firms have fewer than 10 employees or revenues/assets less than \$100,000; *small* firms have fewer than 50 employees or revenues/assets of up to \$3 million; *medium* firms have less than 250 employees *or* a maximum revenues/assets of \$15 million. Our results are consistent across alternative classifications.

[17] In Section 6.3, we extend our analysis to a sample of 10 advanced European economies, including Austria, Belgium, Germany, Spain, Finland, France, Italy, Portugal, Norway and Sweden.

available for very few firms. Our sample has detailed sector classification (up to 4-digit NACE Rev. 2 codes), covering both manufacturing and a number of services sectors.[18]

To address a number of irregularities in the raw data and construct a database that is nationally representative with minimal missing information, we follow an extensive data compilation process, guided by the methods laid out in Kalemli-Özcan et al. (2015), Gopinath et al. (2017), and Gal (2013), among others. Appendix B.1 provides a description of all the cleaning steps and quality checks implemented; some are briefly discussed here. We put together data from several yearly vintages of BvD products (2005, 2010, 2013, 2014, 2017, and 2019) in order to maximize coverage and attenuate the inherent survivorship bias.[19] Before merging vintages together, some basic filters and data harmonization were applied. Then, a thorough cleaning procedure is applied to retain, inter alia, full-year accounting period and one type of accounting standard per firm (mostly unconsolidated), to remove duplicate entries and firm-year observations with basic reporting mistakes such as negative asset or debt holdings. We impose strict consistency checks to ensure balance sheet entries are meaningful and accounting identities hold within a small margin. Observations with negative book's equity are dropped, and due to concerns over data reliability, we only consider firms that have, over the years, a median balance sheet total larger than \$50,000.

In terms of firm-specific financial information, we make use of the following variables: total assets, tangible fixed assets, working capital, cash holdings, all debt items, shareholders' funds, operating revenue, EBIT, cash flows, cost of employees, and material cost. To ensure consistency and comparability across countries and over time, we express all monetary variables in real 2010 dollars.[20] Finally, to limit the influence of outliers and undetected reporting mistakes, we winsorize all firm-level variables for each country and 2-digit sector.

We aim to explore the allocation of credit across firms that differ in their productivity. To this end, two core firm-level measures are needed, namely firms' financial debt positions

[18]Following Lenzu and Manaresi (2019), we exclude firms operating in—2-digit NACE codes in parenthesis: Agriculture (1-3), Mining and quarrying (5-9), Utilities (35-9), Postal services (53), Scientific R&D (72), Education and Health services (85-8), Arts and recreation (90-3), Public administration (84), Households as employers (97-8), Extraterritorial organizations (99), in order to avoid analyzing sectors with high government ownership, and/or due to the difficulties in measuring output; Financial and insurance (64-6) and Real estate (68) where firms are themselves credit providers and heavily regulated; and finally large multinational firms in Tobacco (12) and Pharma (21).

[19]A single-vintage contains a history of up to 10 years of data per firm. But, a firm would disappear from a vintage if it does not report anything in the last 5 years, thus creating a survival bias.

[20]The conversion is done using country-year GDP deflators (with 2010 base) from the World Bank and the 2010 exchange rate of each local official currency to the US dollar.

and revenue TFP. While we do not have matched data at bank-firm-loan level, ORBIS has detailed information on the firms' capital structure. The broadest definition of a firm's debt is its total debt, defined as the sum of current and non current liabilities. With good data coverage, some studies (e.g. Bertrand et al., 2007; Ayyagari et al., 2018) have gone as far using it as a noisy proxy for a firm's bank debt holdings. We do not follow this approach, but use instead the total amount of short-term and long-term interest-bearing debt obligations to financial intermediaries. Financial debt (loans, credits, and bonds) is net of trade credit obtained from suppliers and contractors—an important source of borrowing for small firms (e.g. Petersen and Rajan, 1997)—and excludes other current and other non-current liabilities not payable to credit institutions, but related for instance to provisions, intra-group debts, accumulated trade debt, or income tax payables.[21] Unfortunately, ORBIS does not provide any further split between bank and bond financing. Still, banks in CEE countries are by far the main provider of external funds (Popov and Udell, 2012; Bonin et al., 2014). Also, whereas large firms make greater use of capital markets, SMEs on the other hand, which constitute the vast majority of our data set, have more limited financing options,[22] relying heavily on bank credit and trade credit—the latter is already excluded. Hence, we can plausibly assume that the vast majority of firms' financial debt in ORBIS is bank debt.[23]

As regards productivity, we compute firm-level TFP as a residual from a Cobb-Douglas production function in real value added (VA) with two inputs of labor and capital. Specifically, TFP estimation requires information on real value added (operating revenues - material costs), cost of employees[24] and material costs, all single-deflated by country-sector-year VA deflators, as well as on real capital stock (fixed assets) deflated by country-sector-year GFCF

[21] Financial debt, however, is not perfectly identified in ORBIS. De Socio and Finaldi Russo (2016) notice for the case of Italian firms that a part of financial debt may be wrongly included among other liabilities items. As shown in Appendix Figure B.I, we observe in our data extreme cases where short-term or long-term financial debt is zero for all firms in some country-years. Due to these misreporting issues, we have to exclude observations pertaining to Ukraine in the years 2012–14 and to Romania in the years 2003–9. It is unfortunately hard to establish beyond doubt how precise our measure of financial debt is. Although less accurate, and as of robustness, a firm's total debt yield similar findings—the correlation with financial debt expressed in growth rates is 0.50.

[22] Many empirical studies highlight that European SMEs rarely use market-based funding. From the ECB's Survey on the Access to Finance of Enterprises (SAFE), Barbiero et al. (2020) note that: "of those firms [small and large] that used some form of bank or market financing, 95 percent used bank credit, and only 13 percent used some form of market financing (equity or debt securities)."

[23] A similar assumption is made in other studies using ORBIS such as in Ayyagari et al. (2021), Gourinchas et al. (2022), Barbiero et al. (2020), Giannetti and Ongena (2012), Kalemli-Özcan (2016), Fungáčová et al. (2017), Carbo-Valverde et al. (2016, 2009), McGuinness et al. (2018), among others.

[24] The wage bill captures firms' differences in labor quality (Gopinath et al., 2017).

deflators. As we do not observe firm-level prices, but only 2-digit industry deflators at best, all the productivity measures employed are revenue-based.[25] The input elasticities are estimated based on the control function approach of Olley and Pakes (1996) and Levinsohn and Petrin (2003)—with real material costs as a proxy for unobserved productivity—using the GMM-framework advocated by Wooldridge (2009) and as implemented in a single equation instrumental variables method by Petrin and Levinsohn (2012).[26] We estimate the production function with time dummies separately for each country-sector (2-digit). Appendices A.1 and B.1.5 provide details on the estimation approach and its empirical implementation.[27]

We combine this firm-level data with information on capital flows at an annual frequency based on the IMF's BOP statistics, using both BPM5 and BPM6 versions to maximize coverage. We concentrate our analysis on "gross" capital inflows, i.e. changes in the financial liabilities of a domestic country vis-à-vis nonresidents investors. Distinguishing flows by borrowing sectors following Avdjiev et al. (2014), we focus on inflows of foreign capital to resident banks and the non-financial private sector, while inflows involving the official sector (monetary authorities and the central government) are excluded. More specifically, as we are interested in the effect of foreign capital flows on the provision of credit by domestic banks, we restrict our attention to private gross debt inflows (Calderon and Kubota, 2012; Lane and McQuade, 2014), which comprises most notably other investment debt liabilities[28] (related mainly to cross-border loans), and to a lesser extent portfolio debt liabilities (e.g., bonds and money market instruments)—relative proportions of these two components are shown in Figure 1a. The measure of gross debt inflows to the private sector is expressed as a fraction of nominal GDP. Figure B.I plots this measure for each country in our sample.[29]

[25]Thus, we might confound physical efficiency with market power. As a robustness, we introduce a TFP measure purged from firm- and time-varying mark-ups following De Loecker and Warzynski (2012). We also check robustness using labor productivity (i.e., log of real VA over labor).

[26]This approach does not maintain the assumption of constant returns to scale, corrects for the simultaneous determination of inputs and productivity and the resulting endogeneity bias, and internalizes the Ackerberg et al. (2015) critique on the identification of the labor coefficient.

[27]Measurement errors in firm's TFP are somewhat less problematic as we will compare productivity levels of firms within the same country-industry (Bartelsman et al., 2009).

[28]Other investment are made up of (i) Other equity, (ii) Loans, (iii) Currency and deposits, (iv) Trade credit and advances, (v) Insurance, pension, and standardized guarantees schemes, (vi) Other accounts receivable/payable, and (vii) Special drawing rights (SDR). Given our focus on private debt inflows, we exclude from this measure other equity investment, SDR allocation, and IMF lending. Cross-border bank loans fall into other investment and take the lion's share of this category, not only capturing direct cross-border loans to non-bank private borrowers or non-affiliated banks (inter-bank flows), but also cross-border lending to affiliated banks (subsidiaries in the recipient country).

[29]As robustness, we also rely on narrower measures based on the BIS's cross-border bank positions.

After applying all these procedures and exploiting information on firms' TFP, we are left for our 12 CEE countries with roughly 3.3 million observations for 747,097 firms during the period 2003–2017. From this large sample, where industries' median productivity are computed, we then impose further data requirements and form three samples utilized in our empirical analysis that differ with respect to the definition of a firm's financial debt annual change as the dependent variable. Each sample is defined in Appendix B.1.6. For instance, when further conditioning on observing firm-level controls and changes in firm's financial debt at both the intensive and extensive margins (sample B), the sample shrinks to an unbalanced panel comprising 1,022,404 firm-year observations with 222,376 unique firms.

3.2 Summary Statistics and Stylized Facts

We provide a description of our four samples of analysis in Tables B.1-B.5 in the Appendix. Table B.1 shows that Croatia, Serbia and Czech Republic account to about 46% of firm-year observations, while only about 7.5% is drawn jointly from Bosnia-Herzegovina, Hungary and Romania.[30] Most of observations are concentrated in post-2005 years (Table B.2). As shown in Table B.3, our final samples include firms from 53 NACE 2-digit sectors, with most of them operating in wholesale and retail trade (roughly 37% of firm-year observations), followed by the manufacturing sectors (26%) and construction (10%). SMEs represent around 90% of firms in our samples, mainly composed of small (about 65%) and medium (21%) firms, while the coverage of micro firms is significantly reduced on the condition that firm's financial debt is reported (Table B.4). Table B.5 reports averages of some firm-level variables across SMEs and large firms, while Table B.6 presents pooled summary statistics.

To get an indication of the actual coverage with respect to the whole population of firms, we compare our final samples against official Structural Business Statistics (SBS) census data in terms of gross output (or turnover) and employment.[31] We distinguish two samples here.

[30] This uneven distribution does not necessarily stem from differences in the size of countries' corporate sector. While firms' reporting in Europe is mandatory, requirements—in terms of who reports and what to report—are not homogeneous across countries (Kalemli-Özcan et al., 2015). Also, some data cleaning procedures are more restrictive for some countries (e.g. for Romania and Ukraine).

[31] Following Kalemli-Özcan et al. (2015), for a given country-year cell, we compute the ratio of the aggregated gross output produced by the firms (either all, SME or large) in our final samples to official values across those sectors for which gross-output is available in both data sets. A similar procedure is adopted in terms of employment. Then for each country, we take the average of these ratios over 2003–2017. Regarding firm size distribution, we report for each country the 2003–2017 average share of indicated firm size category's gross output from the relevant data sources.

As shown in Appendix Table B.7, using our largest sample D based solely on the availability of firm's TFP, our data account for roughly 53% of the official gross output and 45% of employment on average across all countries. If we impose further data restrictions on the availability of firm-level controls and the consistent reporting on changes of financial debt positions, being the most critical variable in this regard, our sample of analysis B covers on average 26% and 21% of aggregate official output and employment, respectively. Large firms (i.e., firms with more than 250 employees in both data sources) are better represented with roughly 1.6 times larger coverage than SMEs.[32] In terms of the fraction of economic activity captured by firms belonging to SME or large categories, our data broadly match the official size distribution, where most of the gross output are accounted for by SMEs.[33]

The economies of the CEE countries provide a valuable laboratory to explore over a full boom-bust economic cycle the domestic bank intermediation of cross-border capital flows, and to which type of firms they are channeled to. We lay out some basic stylized facts in Figure 1. Amid ample global liquidity prior to 2008 and driven by a process of rapid economic and financial integration with the European Union, CEE became a "destination of choice" (Bakker and Gulde, 2010). These countries attracted large capital inflows to the private sector, with gross private debt inflows (mainly composed of other investment) averaging 8.19% over 2003–2008 (Fig. 1a).[34] Bank credit to the private sector (Fig. 1b) grew year-on-year at an average of 24.76% in real terms during 2005-2008 (while in Euro area at 4.86%). This credit boom came to an abrupt end with the onset of the global financial crisis and the ensuing sovereign debt crisis. CEE countries saw a strong reversal of bank inflows resulting in a stall in total credit growth, severe GDP contractions and a modest recovery until 2017. As regards the quality of credit allocation (Fig. 1c), aggregate indicators show that the relative difference in risk between firms with highest and lowest debt change rose significantly in the pre-crisis years (i.e., the firms whose credit is growing the fastest have become riskier relative to bottom debt-takers), then declined and reached a trough in 2012, and had risen constantly since then; with almost an opposite trend as regards the productivity

[32] While unreported, the coverage difference with micro firms is far more acute. Micro firms are clearly underrepresented in our data because of limited reporting requirements, especially as regards financial debt holdings. Of note, our results are consistent if we exclude micro firms from our samples.

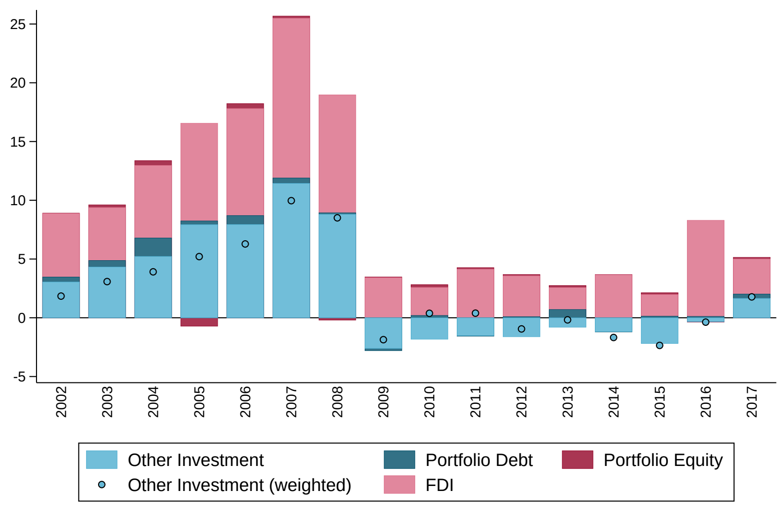
[33] We apply in Section 6.3.2 several weighting schemes to mitigate concerns arising from an uneven distribution of country-year observations and from under-representation of certain firms and industries in a given country. This exercise leaves our conclusions largely unchanged.

[34] Much of this new funding took the form of cross-border loans from Western European banks to their own subsidiaries (in 2007, foreign-owned affiliates held on average 76% of local banking assets).

dimension. Finally, in terms of allocation of inputs (Fig. 1d), the within-industry dispersion in log MRPK had been increasing sharply on average in the CEE region since 2005, especially in the services sectors, while the dispersion in log MRPL remained more stable, consistent with the evidence in Giordano and Lopez-Garcia (2018) for a sample of 9 CEE countries.

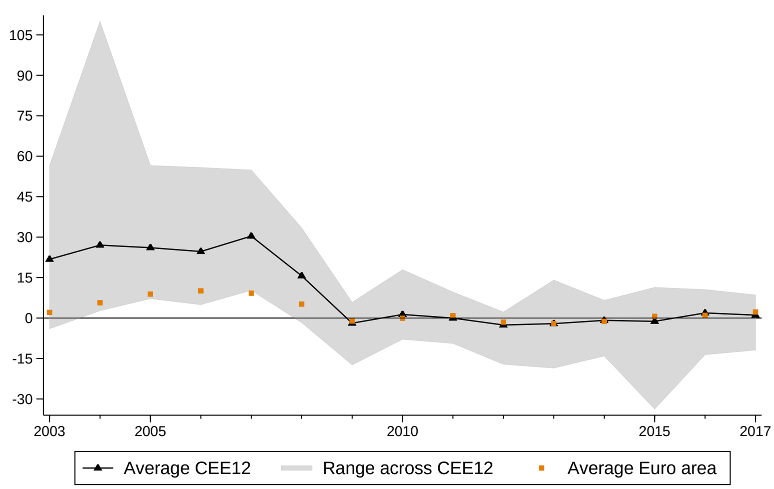
Figure 1. Macro-Financial Developments, Pooled Sample of 12 Emerging Economies (CEE12)

(a) Total Inflows to the Private Sector by Main Types (*in % of nominal GDP*)
Sources: IMF's BOP, authors' calculations.



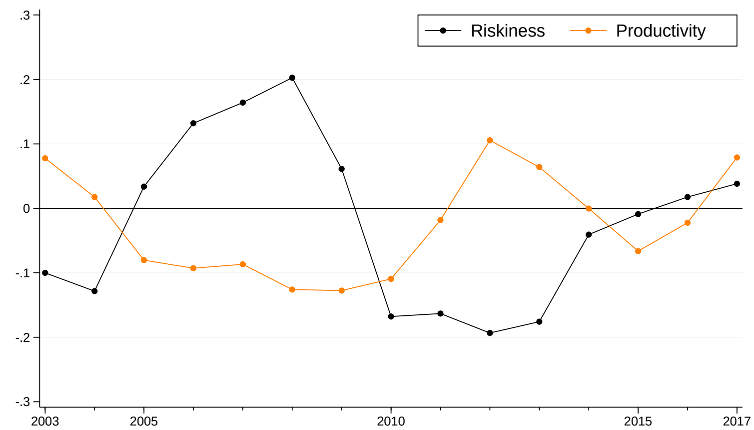
Note: Total regional capital inflows are based on IMF's BOP data, which include flows to banks and to the non-financial private sector. We focus on "gross" flows coming from non-residents (liability side). We take for each year-component the simple unweighted average across our 12 countries—we also show other investment regional flows weighted by countries' GDP.

(b) Real Credit Growth to Private Sector (*in %*)
Sources: IMF's IFS, authors' calculations.



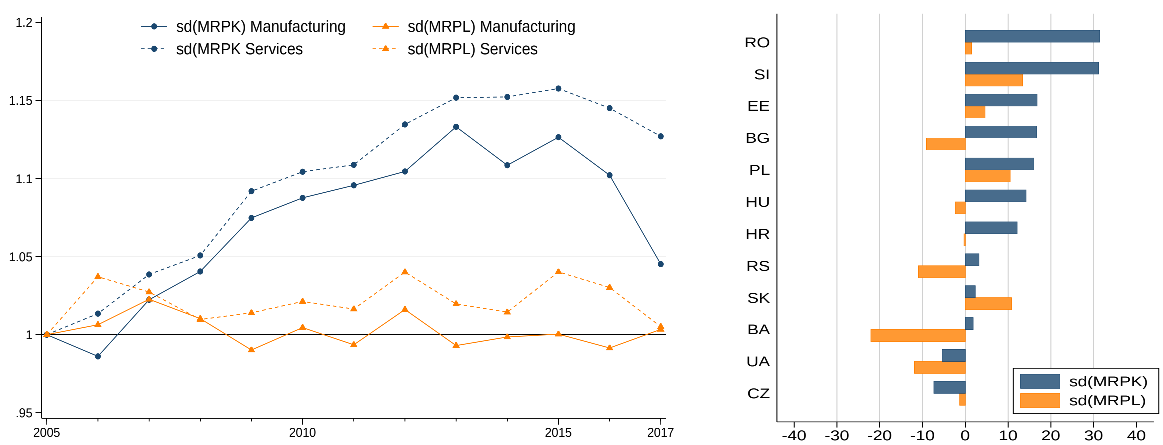
Note: Data on the stock of credit in local currency granted by domestic deposit money banks to resident private sector are from the IMF's International Financial Statistics (IFS), line FOSAOP/22D. For Estonia, Slovenia and Slovakia, we have complemented missing values at the beginning of the sample period with data taken from Eurostat based on "Private sector debt, LCU", which is not limited to claims of deposit money banks. Year-on-year growth rate series are deflated by their corresponding CPI changes, also from the IMF' IFS. We take for each year the simple unweighted average across our 12 countries.

(c) Within-Industry Credit Allocation, Riskiness and Productivity *(indexes)*
Sources: ORBIS, authors' calculations.



Note: These measures build on the approach by Greenwood and Hanson (2013), IMF (2018) and Brandao-Marques et al. (2019). The indicator of the riskiness of credit allocation is computed as the difference in the average risk decile (in terms of -1*Altman's Z score) between the quintile of firms whose interest-bearing debt increase the most relative to the quintile of firms with the lowest debt increases. We obtain similar patterns if we consider instead firms' leverage or debt overhang (with correlation > 0.84). Similarly, we construct a measure of credit allocation quality that compares the relative TFP between firms with the highest and lowest debt increases. It follows that a higher value of the indicators means that on average the firms whose credit is growing the fastest have become riskier, or more productive, relative to bottom debt-takers. We compute these indexes for each country-year-sector (2-digit), with more than 50 firms per cell, thus focusing on the within-industry credit allocation. We then take for each country-year a weighted average across sectors, using sectoral average VA shares from National Accounts as time-invariant weights. Finally, the historical average for each country is subtracted, and we obtain the regional aggregate yearly measure by taking the median value across our 12 countries. Data are shown as simple two-year moving averages.

(d) Within-Industry Dispersion in MRPK and MRPL *(left, 2005=1 ; right, % change 2005-17)*
Sources: ORBIS, authors' calculations.



Note: Based on Hsieh and Klenow (2009) model, input misallocation can be measured, albeit imperfectly, by the dispersion in the marginal productivity of inputs across firms within a sector. In the absence of distortions in the economy, the returns to capital and labor would be equalized across firms within the same sector, as firms face the same marginal costs. Under certain restrictive assumptions, Hsieh and Klenow show that sectoral physical TFP is lower, the higher the dispersion in revenue TFP across firms, which is in turn a function of the dispersion in MRPK and MRPL (and their covariance), and ultimately a result of capital and labor distortions. The firm marginal products are computed as $MRPK_{ist} = \frac{\alpha}{\mu}\frac{p_{ist}y_{ist}}{k_{ist}}$ and $MRPL_{ist} = \frac{1-\alpha}{\mu}\frac{p_{ist}y_{ist}}{l_{ist}}$, where $p_{ist}y_{ist}$ is nominal value added, k_{ist} fixed assets and l_{ist} the wage bill. Our measures of dispersion of factor returns use within-industry variation of firm outcomes and thus, algebraically due to the log transformation, are not influenced by the assumption of constant returns to scale, nor that the output elasticities α and markup μ are homogeneous across industries, nor to the use of industry-level price deflators, as long as these metrics do not vary within a given industry. Following Kehrig (2015), we correct firm-level MRP measures from country-industry specific growth trends, and then normalize them. For each country-year, we compute the standard deviation of log MRP across firms within a given 2-digit sector, with at least 10 observations. These dispersions are aggregated at country-year or country-broad sector-year level, by taking a weighted average across sectors. We absorb the country dimension by taking the median value of dispersions across countries.

3.3 Empirical Approach

3.3.1 Model Specification

We shed light whether capital inflows affect differentially the credit growth of ex-ante low productive firms relative to their more productive industry peers. We test this hypothesis by estimating the following panel-based fixed-effects model:

$$\Delta \ln(y_{i,t}) = \alpha + \sum_{q=0}^{2} \beta_q \left(D_{i,t-1}^{TFP} \times CF_{c,t-q} \right) + \gamma D_{i,t-1}^{TFP} + \theta_l X_{i,t-1}^{l} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t} \quad (1)$$

where i indexes firms, j industries at the four-digit level, c countries and t years. The dependent variable $\Delta \ln(y_{i,t})$ is the log-difference of outstanding financial debt (loans and bonds) of firm i in year t. $CF_{c,t-q}$ is the private debt inflows of country c normalized by its GDP and enters the regression contemporaneously and up to two year lags, so as to capture its delayed impact on domestic lending to the private sector (see e.g., Sá et al., 2014; Davis, 2015; Aldasoro et al., 2020). $D_{i,t-1}^{TFP}$ is a time-varying firm-level dummy that is equal to 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year and size class (SME, large) level.

The specification also includes several firm-specific characteristics to account for common determinants of firms' financing decisions and banks' lending decisions, that may influence firms' observed credit growth. The vector of firm-level controls X_i^l is dated in t-1 to limit endogeneity issues. Specifically, it includes *firm size* defined as the logarithm of total assets, *collateral* proxied as the ratio of tangible fixed assets to total assets, *profitability* defined as earnings before interest and taxes (EBIT) divided by total assets, *growth opportunities* measured as the ratio of intangible assets to total assets,[35] *external financial need* computed as 1 minus the maximum rate of growth that could be internally financed,[36] and continuous *log-TFP* as previously defined (i.e., revenue-based, with elasticities estimated at country-2digit sector level). The model is saturated with α_i, $\alpha_{c,s}$, $\alpha_{s,t}$, $\alpha_{c,t}$, which denote firm, country-industry, industry-year and country-year fixed effects, respectively.[37]

[35] Our results are unchanged if we rely instead on firm's real sales growth. Both measures can be considered as alternatives to Tobin's Q for listed firms (i.e., the market-to-book ratio of total assets).

[36] We use this measure to partly account, along with other controls, for a firm's demand for credit; precisely the credit that would be demanded for the growth in excess to the one that could be internally financed (Di Mauro et al., 2018). Following Demirgüç-Kunt and Maksimovic (1998) and Guiso et al. (2004), a firm's maximum rate of internally financed growth is obtained using Higgins (1977)'s micro-founded approach as $ROA/(1 - ROA)$, where ROA is the return on assets.

[37] Industries are classified according to four-digit NACE Revision 2 codes. Results are robust to more

Our coefficient of interest $\beta \coloneqq \sum_{q=0}^{2} \beta_q$, captures an interaction between a country-specific capital flow variable and a firm-level indicator distinguishing between high- and low-TFP firms within the same sector.[38] Given the presence of firm fixed effects, our source of identification relies on the within-firm time variation of firm's debt growth and capital inflows, that is within a firm, how firm's debt growth relative to its lifetime average varies in years when capital inflows increase. It is the interaction of capital inflows with the firm-productivity dummy that allows us to identify how the within-firm effect of capital inflows on financial debt change differs across firms of different productivity, and from the way we define the TFP dummy, to investigate in particular whether higher capital inflows lead to increased credit growth of ex-ante low-TFP relative to high-TFP firms within the same industry-country-year and size class. A negative value of β would imply a within-industry allocation of credit titled towards low productivity firms when capital flows into the country.

Eq. (1) is estimated using OLS with standard errors clustered at the industry-year level which allow for observations within the same industry-year across firms to be correlated, but assume independence across clusters.[39]

3.3.2 Identification Challenges

The key identification challenge in Eq. (1) is to identify the credit supply effect induced by capital inflows. Common measures, such as financial debt granted, are equilibrium outcomes of both the bank's supply—the likely greater willingness of banks to extend credit to low or high-productivity firms when liquidity flows—and the firm's demand—the likely greater willingness and ability of these firms to seek more funding at times of capital inflows. While a bank-firm loan-level dataset would provide the possibility to include firm-year fixed effects to rigorously control for unobserved and time-varying firm fundamentals that are correlated

aggregate definition of industries.

[38] Alternatively, the interaction with a continuous measure of firm-level TFP focuses essentially on within-firm dynamics, in that a negative coefficient β would indicate that the effect of capital inflows on firm's debt growth decreases as TFP increases within-firm. Thus, unlike our baseline specification, this estimation does not, strictly speaking, shed light on the heterogeneous impact of capital inflows across firms with different productivity within the same industry. Furthermore, using TFP in the form of a dummy a) smooths to a certain extent the impact of outliers and potential measurement errors, b) smooths jumps in within-firm TFP, as we compare the firm TFP with its industry median for both $t-1$ and $t-2$, and c) gives a straightforward interpretation of the coefficient.

[39] Our treatment variable is at the country-year level, but it is interacted with a firm-level variable. Our results are robust to a range of alternative standard errors, that are either clustered at the country-year level, at the country-industry level or using two-way clustering (Petersen, 2009) at the firm and at each one of the dimensions aforementioned. Results could be made available upon request.

with credit demand, our approach based on firm-level data nevertheless provides a way to partly address the usual criticism that unobserved credit demand shocks might contaminate our coefficients (Degryse et al., 2019; Ongena et al., 2016).[40]

The inclusion of fixed effects and firm controls in our specification helps tease out the identification of supply-driven effects induced by capital inflows. Controls at the firm-level aim to capture time variation in firms' performance and creditworthiness so as to control for observable time-varying firm credit demand. Firm fixed effects, in turn, soak up any time-invariant firm characteristics affecting loan demand. Additionally, the inclusion of country-year and industry-year fixed effects not only helps absorbing the impact on firms' debt financing decisions of changing country and sector conditions, but also helps controlling for unobserved time-varying aggregate and local demand conditions. Country-year fixed effects absorb any changes in country-level demand conditions, including those arising from changes in general uncertainty conditions for instance. Industry-year fixed effects absorb the impact of changes in credit demand for the narrow four-digit sector that our firms operate in.

Hence, the identifying assumption requires that firms with ex-ante high TFP are subject to similar local demand shocks as low-TFP firms within the same four-digit industry and any remaining variation in unobservable firm-specific credit demand does not vary systematically by the firm's productivity. While in principle firm demand could exhibit heterogeneity within industries, we assume that most credit demand fluctuations are driven by industry and country specific factors (e.g. Degryse et al., 2019; Acharya et al., 2019; Yesiltas, 2015; Ferrando et al., 2019), and not idiosyncratic firm factors, and thus we postulate that it is of second order importance and are unlikely to bias much our differential effect estimates.[41]

[40] Loan-level studies require privileged access to credit registry data and are usually based on a single country (e.g. Jiménez et al., 2012, 2014; Morais et al., 2019). Following Khwaja and Mian (2008)'s methodology, estimation with firm-year fixed effects compares the same firm borrowing from different banks in a given year, which clearly enhances identification, but focuses on the subgroup of borrowers having multiple banking relationships in a given year. If these firms are not representative for the full sample of borrowers, this strategy might introduce sample selection effects, especially among SMEs, and for emerging markets where the fraction of multiple bank borrowers is low (see e.g. Altavilla et al., 2020). For instance, Degryse et al. (2019) replace firm-time fixed effects with industry-location-size-time fixed effects to control for firm-level credit demand. They argue that bank-loan supply shocks based on the sample of multiple-relationship firms are significantly different from shocks based on the full sample of firms, given the differences in borrower characteristics (e.g. size, age). See also the cross-country analysis by Ongena et al. (2016), which employs higher levels fixed effects (at country and industry) and observable firm characteristics.

[41] For instance, results in Morais et al. (2019) suggest that a specification with firm and state-industry-year fixed effects works reasonably well in controlling for borrower fundamentals compared to a specification with firm-year fixed effects. Unreported results confirm the robustness to the inclusion of firm dummies combined with interacted country-industry-year fixed effects. By controlling for time-varying demand changes for each

Note that the level of capital inflows is absorbed by country-year dummies as any other domestic macroeconomic variables that could affect firm's debt growth. While we control for the average effects of all shocks at the country-level, admittedly these shocks might also have a differential effect on high relative to low TFP firms. Hence, we might spuriously confound the differential effects of capital inflows with the ones induced by other macroeconomic variables, challenging our interpretation of regression coefficients as causal. Accordingly, we also attempt in the Robustness Section to isolate the supply-side component of capital inflows that is not driven by domestic pull factors.

3.3.3 Different Specification Variants

Analogously to Eq. (1), in which capital inflows are simultaneously introduced in period t and up to 2 year lags, most of our empirical analysis is nonetheless conducted, for ease of exposition, using a specification in which capital inflows enter as a moving average of contemporaneous and the past 2 years, that is:

$$\Delta \ln(y_{i,t}) = \alpha + \beta\Big(D^{TFP}_{i,t-1} \times CF_{c,MA,t,t-2}\Big) + \gamma D^{TFP}_{i,t-1} + \theta_l X^l_{i,t-1} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t} \tag{2}$$

Also, our estimates of β are only informative about the relative, as opposed to absolute, effects of capital inflows on credit growth across the low and high TFP firms, as the overall effect of capital inflows is absorbed by the country×year dummies. To put the differential effects β into perspective, we occasionally resort to a regression specification of the form:

$$\begin{aligned}\Delta \ln(y_{i,t}) = \alpha + \beta\Big(D^{TFP}_{i,t-1} \times CF_{c,MA,t,t-2}\Big) \quad &+ \quad \zeta CF_{c,MA,t,t-2} + \gamma D^{TFP}_{i,t-1} + \theta_l X^l_{i,t-1} \\ &+ \quad \theta_m MC^m_{c,t,t-2} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \epsilon_{i,t}\end{aligned} \tag{3}$$

where $\alpha_{c,t}$ is replaced by a vector of country-level control variables $MC^m_{c,t,t-2}$.[42]

Departing from the log-difference of financial debt, we also consider alternative dependent variables that accommodate changes in credit along both the intensive margin—continuing credit flows to firms already indebted—and the extensive margin of lending—credit flows to

industry in each country, the identifying assumption becomes in this case that loan demand by all firms within the same industry-country changes equally.

[42] We add the usual suspects that are related to credit growth, evaluated in t and up to 2 lags: real GDP growth rate, consumer price change, change of nominal exchange rate, unemployment rate, trade-to-GDP ratio, and stock market returns (sources: World Bank's WDI and GFD). Other controls like log real GDP per capita and its square term, broad money-to-GDP ratio, and the Chinn and Ito's financial openness index were not statistically significant and excluded for parsimony.

new borrowers or credit flow disruptions due to borrowers exiting.

We analyze all credit flows with the measure developed by Davis and Haltiwanger (1992) and Davis et al. (1996) in their analysis of establishment-level employment dynamics.[43] The annual change in a firm's financial debt is computed as the change in credit between two consecutive periods over an average of credit volume in each period, that is $(y_{i,t} - y_{i,t-1})/0.5(y_{i,t} + y_{i,t-1})$. Like the log-difference, this modified growth rate is a symmetric measure, but has the added advantages that it accommodates debt positions that are equal to zero and is bounded in the range of [-2,2], which limits the influence of outliers. Extensive margin changes take place at the extremes of this interval,[44] and are thus assigned greater weights in OLS.

We also introduce a third dependent variable which is computed as the firm's change (first-difference) in financial debt from the previous period scaled by lagged total assets, that is $\Delta y_{i,t}/TotalAssets_{i,t-1}$. As opposed to the two previous growth rates that focus on the relative changes of a firm's debt in response to capital inflows, this new measure provides a different scale; the flow of debt is measured here as the absolute change in a firm's proportion of debt in its capital structure.[45] Hence, it looks at absolute changes of a firm's debt in response to capital inflows, but expresses these absolute changes in perspective with the firm's total assets, so as not to emphasize growth of debt in larger firms. Similar to the mid-point growth rate, this measure also accommodates intensive and extensive changes, but treats credit adjustments at the extensive margin differently. First, extensive changes are not over-weighted in the OLS regressions (i.e., the first-difference of debt receives the same treatment at both margins), unlike for the mid-point growth rate for which the distribution of the outcome variable display mass points at values -2 and 2. Second, the relative magnitude of extensive changes, that is the amount of credit committed at time of entry (or credit volume lost at time of exit), relative to the firm's total assets, is accounted for in the estimation.[46]

[43] Henceforth, this measure is referred to as the DHS modified or mid-point growth rate. This growth rate has become standard for the analysis of firm, labor market and trade dynamics, in settings where entry/exit and the proportion of zeros are significant.

[44] If a firm has zero debt in $t-1$ and positive credit in t, then the DHS modified growth rate takes value 2. Conversely, exits ($y_{i,t-1} > 0$ and $y_{i,t} = 0$) result in a growth rate of -2.

[45] This third measure might prove particularly useful to assess the economic effect in cases where the growth rate of debt is large but insignificant relative to the size of a firm's balance sheet.

[46] For instance, this measure would distinguish a low TFP firm borrowing 1000$ at times of entry from a 10000$ loan for a high TFP firm. Conversely, the mid-point growth rate is silent about the net change in the average loan to new borrowers, and would assign irrespectively a growth rate of 2.

4. Benchmark Results: Capital Inflows and Credit Growth

Our analysis investigates the financial sector ability, at times of capital inflows, to channel credit to its most productive use. We first present our benchmark results on the effect of debt inflows on the intensive margin of credit growth across firms with different productivity within the same industry, and then put these differential effects into perspective. We take next a more expansive view by estimating jointly the intensive and extensive (entry into and exit from credit markets) margins in two other outcome variables for a firm's flow of credit.

4.1 Intensive Margin Adjustments

4.1.1 Basic Results

Table 1 presents the regression results from estimating Eq. (1) in which the log difference of firms' financial debt is regressed on capital inflows interacted with a productivity dummy that distinguishes high from low TFP firms. All columns contain firm, country-industry, industry-year and country-year fixed effects as well as firm controls. With a delta-log approximation, the expected values of the dependent variable are intended to be conditional on firms' debt being positive in both t and $t-1$, thus this specification focuses on the intensive margin of credit growth. We emphasize that our interest is not in the individual effects of the contemporaneous and different lags of CF, but rather in its cumulative impact, that is on the sum of the interaction term coefficients ($\sum_{q=0}^{2} \beta_q$), which are reported in bold in Table 1.

Starting with the whole sample of firms, column (1) shows the baseline results wherein the productivity dummy $D_{i,t-1}^{TFP}$ uses as cut-off the median log-TFP defined within the same country-industry-year and in the same size class (SME, large). The sum of the estimated coefficients for our main interaction terms is negative and strongly statistically significant at the 1 percent level, suggesting that debt inflows disproportionately raise the credit growth rates of ex-ante low TFP firms relative to their more productive industry peers. In economic terms, all things equal, a 1 percentage point cumulative increase of inflows in country c raises the annual credit growth rates of low TFP firms by 0.265 percentage point more than of high TFP firms within a given sector. This differential is not trivial against the background of a 0.8% average and a -3.5% median annual credit growth rate and that a one standard deviation of debt inflows in the sample amounts to 5 percentage points.

Next, in columns (2) and (3), we decompose our full sample of firms into subsamples

Table 1. Firm's Debt Growth and Capital Inflows

Dependent variable: **$\Delta\ln(y_{i,t})$, y=Financial Debt**	**All**	**SME**	**Large**	**All (pool)**
	(1)	(2)	(3)	(4)
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,t}}$	-0.032	-0.036	-0.014	-0.029
	(-0.67)	(-0.71)	(-0.10)	(-0.61)
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,t-1}}$	-0.116^{**}	-0.120^{**}	-0.176	-0.101^{**}
	(-2.23)	(-2.22)	(-1.08)	(-2.02)
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,t-2}}$	-0.117^{***}	-0.128^{***}	-0.058	-0.135^{***}
	(-2.67)	(-2.75)	(-0.42)	(-3.15)
$D^{TFP}_{i,t-1}$	0.021^{***}	0.021^{***}	0.024^{**}	0.023^{***}
	(4.75)	(4.39)	(1.98)	(5.20)
$\mathrm{TFP}_{\mathrm{i,t-1}}$	0.049^{***}	0.051^{***}	0.035^{***}	0.048^{***}
	(11.24)	(11.26)	(2.87)	(11.29)
$\mathrm{Collateral}_{\mathrm{i,t-1}}$	-0.256^{***}	-0.270^{***}	-0.034	-0.251^{***}
	(-21.23)	(-21.39)	(-1.00)	(-20.87)
Ext. Financial $\mathrm{Need}_{\mathrm{i,t-1}}$	-0.053^{**}	-0.063^{***}	-0.033	-0.052^{**}
	(-2.52)	(-2.87)	(-0.57)	(-2.48)
Firm $\mathrm{Size}_{\mathrm{i,t-1}}$	-0.263^{***}	-0.268^{***}	-0.241^{***}	-0.261^{***}
	(-63.96)	(-62.09)	(-24.32)	(-64.07)
Growth $\mathrm{opp.}_{\mathrm{i,t-1}}$	0.001	-0.002	0.093	0.019
	(0.01)	(-0.04)	(0.46)	(0.38)
$\mathrm{Profitability}_{\mathrm{i,t-1}}$	0.545^{***}	0.521^{***}	0.682^{***}	0.542^{***}
	(13.46)	(12.15)	(7.71)	(13.62)
Firm FE	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes
Country-Industry FE	yes	yes	yes	yes
Country-Year FE	yes	yes	yes	yes
◇ H_0: Σ $D^{TFP}_{i,t-1}$×$\mathrm{CF}_{\mathrm{t-q}}$=0	**-0.265^{***}**	**-0.285^{***}**	**-0.249**	**-0.265^{***}**
(t-stat)	**(-5.05)**	**(-5.07)**	**(-1.60)**	**(-5.09)**
◇ Exclusion test	11.010^{***}	11.000^{***}	1.290	11.710^{***}
(p-value)	(0.000)	(0.000)	(0.280)	(0.000)
Observations	826217	738657	86656	842057
Number of firms	183521	166907	16466	185377
R^2	0.283	0.289	0.280	0.283
Within Adj. R^2	0.024	0.025	0.018	0.024
Dep. var. avg;p50 (in %)	0.8;-3.5	0.2;-4.3	5.7;0	0.8;-3.5
#firms D^{TFP} (p1;p10;p50)	40;154;968	63;244;1130	31;45;147	71;268;1199

Note: This table reports the results of estimating $\Delta\ln(y_{i,t})=\alpha+\sum_{q=0}^{2}\beta_q\left(D^{TFP}_{i,t-1}\times CF_{c,t-q}\right)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of outstanding financial debt of firm i in year t. D^{TFP} is a time-varying dummy that is equal to 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year and size class (SME, large) level, except in column (4) that is irrepective of firm size class. *CF* is the private debt inflows of country c normalized by its GDP and enters the regression contemporaneously and up to 2 year lags. Firm controls X lagged one year include: collateral (tangible fixed assets/total assets), firm size (log of total assets), profitability (EBIT/total assets), external financial need (1- ROA/(1-ROA)), growth opportunities (intangible assets/total assets) and log-TFP (revenue-based, elasticities estimated at country-sector level). All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level.*** $p<0.01$, ** $p<0.05$, *$p<0.1$.

of SMEs and large firms, respectively. Column (2) indicates that the differential pattern in debt growth titled towards low productive firms is mainly driven within the SME subsample, which is not surprising considering that SMEs make up the bulk of observations—and thus somewhat redundant with column (1) results. By contrast, in the (substantially smaller) subsample of large firms, the sum of the interaction coefficient terms are also negative, but their estimated magnitude are more modest than within SMEs and fail to reach statistical significance (t-stat -1.60) because of large standard errors—given that both the sample size and the difference in effects are smaller, the test has less statistical power to detect such difference. Still, after constraining the error variances to be equal across the SME and large firms groups, we cannot reject the null for the equality of the differential effect coefficients across the two groups (Wald test p-value=0.86).

Finally, column (4) analyzes also the whole sample of firms but, as opposed to column (1), the cut-off to differentiate low versus high TFP firms is computed solely at the country-industry-year level, thus pooling all firm sizes together. Gopinath et al. (2017) emphasize that capital flows lead to an increase in MRPK dispersion across firms, especially between small and large firms, and not within large firms. We still find a strong negative and statistically significant differential effect with this setting.

Regarding the firm-level controls, in general, a within-firm increase in firm size, an increase in pledgeable assets or higher external financial need[47] are associated with lower debt growth, while in years when lagged profitability and TFP are higher than their firm-level averages, firm's debt tend to grow more. Their inclusion serve primarily to wipe out part of the firm-specific demand conditions and to control for growth convergence-type effects. Note that we do not pay serious attention to the estimated coefficient on the time-varying productivity dummy D^{TFP} as its identification with firm fixed effects rests on the small number of firms that ever switches from one TFP bin to the other.[48]

For robustness, Table C.1 in the Appendix show that these first results are not confined

[47]The negative estimates on the external financial need variable are somehow surprising considering that firms with smaller growth through internal resources, i.e., those with a lower ROA, would demand more credit. Yet, the return on assets is commonly used in banks' credit assessments, thus we might be capturing the confounding supply effects that banks are in general less willing to extend credit when a firm's ROA deteriorates. At the same time, it is worth noting that our extensive set of fixed effects controls as well for a firm's credit demand, and that some of the firm-specific control variables are relatively highly correlated with each other. We confirm results on our main interaction term for specifications with a more restrictive set of firm controls. Results are available on request.

[48]The TFP dummy is highly persistent within firm, with only 38,918 switchers out of 183,251 firms.

to one particular functional form with respect to the timing of capital inflows. In order to capture the delayed impact on domestic lending to the private sector (see e.g., Sá et al., 2014; Davis, 2015; Aldasoro et al., 2020), we introduced simultaneously in Eq. (1) capital inflows contemporaneously and up to 2 year lags.[49] When lags of capital inflows are included separately in columns (2-4), each lag on the interaction term is negative and strongly statistically significant, albeit to a less extent in magnitude for the contemporaneous one. We introduce in columns (5-6) capital inflows as a moving average of contemporaneous and up to 2 lagged years. Notice that estimates on $CF_{\text{MAt,t-2}}$ in column (6) are close to the sum of estimated coefficients of the interaction terms when including all lags together in column (1). For convenience and clarity throughout the rest of the paper, and since we are interested in the overall impact of capital inflows, we will focus henceforth on the model in Eq. (2) where capital inflows are measured as the moving average of contemporaneous and the past 2 years.

4.1.2 Absolute Effects and Alternative TFP Cutoffs

Note that our identification is based on the differential effects of capital inflows within country-industry across firms varying in their ex-ante productivity. While country×year fixed effects give us more certainty about the "causal" impacts of capital inflows on firms' debt growth, a drawback of this approach is that our estimates are only informative about the direction of these effects on the relative, as opposed to absolute, growth rates of debt across the low and high TFP firms; the overall effect of capital flows is subsumed in the country×year fixed effects. We can gain some insights on their signs and infer—with caution—their absolute magnitude by removing the country-year dummies, but including a set of macroeconomic controls to limit the risk of an omitted variable bias, as specified in Eq. (3).

Table 2 in Panel A shows that the absolute effects of capital inflows on debt growth are always positive—higher capital inflows increases credit growth—and as we have previously shown, this additional credit is allocated to a larger extent towards the least productive firms. More importantly, these attendant results help us put into perspective the magnitude of the

[49] Another reason initially was to look at the dynamic impact of capital inflows on credit allocation, since the efficiency of credit allocation might be different from its initial shock to its lasting effect: initially bank might finance the most productive projects but at some point, faced by an inflow of liquidity, start lending to riskier projects or become less scrupulous on the quality of projects being financed. However, it is hard to draw any conclusions on its dynamic impact because capital inflows tend to be serially correlated, making it difficult to interpret the individual effects of our interaction of interest and to contrast the contemporaneous response with its different lags.

relative effects. Does this skewed allocation of credit at times of inflows imply a crowding out of bank credit to the most productive firms? On the contrary, it turns out that, in absolute terms, capital inflows expand growth in financial debt for both low *and* high TFP firms. Although the effects of capital inflows on the relative debt growth rates are non-trivial and similar in magnitude from previous evidence, the observed differences appear certainly much less striking on an absolute scale: in the sub-sample of SME firms (column 4), the main effect of capital inflows on debt growth for high TFP firms is 1.540 percentage points, while the additional effect for low TFP firms is 0.338 percentage point higher at 1.878.

Moreover, we find that large firms also benefit from higher credit growth rates following capital inflows, although the main effects (column 6) are much smaller in magnitude compared to SME firms, congruent with the general perception that smaller firms are more reliant on bank financing for external funds (e.g., Berger and Udell, 2002), more financially constrained (e.g., Beck et al., 2005; Beck and Demirgüç-Kunt, 2006), and as such tend to have higher shadow value of financing and are likely to benefit disproportionately more from better access to finance (e.g., Gertler and Gilchrist, 1994; Laeven, 2003; Rice and Strahan, 2010).

Finally, to further put these differentials into perspective, we now refine the comparison between the lowest and highest productive firms within the same industry. Panels B and C of Table 2 report our estimated interaction of interest at different cut-off values for the D^{TFP} dummy, by comparing the lower and upper thirds in panel B, and quartiles in panel C of the TFP distributions—again at the country-industry-size-year level. As we move away from the median towards the tails, the negative differential effects become more pronounced in terms of both statistical significance and substantive magnitude. For instance, for the SME subsample, the estimated differential increases monotonically in value as the percentile cut-off becomes more selective, from an estimate of -0.296 for the median cutoff to -0.487 when comparing the highest to lowest quartiles. On average, based on estimates in column 3 of panel C, in a country experiencing a 5 percentage points increase in debt inflows, the difference in debt growth between an average firm in the lowest quartile and one in the upper quartile of the TFP distribution within the same industry is -2.43 percentage points. Where nontrivial differences between TFP halves were detected, results confirm that these are not entirely driven by firms with near median TFP, but hold and become larger as we compare the least from the most productive firms at the tails of the TFP distribution.

Table 2. Firm's Debt Growth and Capital Inflows, Direct Effects and Finer TFP Cut-offs

Dependent variable: $\boldsymbol{\Delta}\ln(\boldsymbol{y_{i,t}})$	**All**		**SME**		**Large**		**All (pool)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A TFP cutoff : p50								
$D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}$	-0.276***	-0.307***	-0.296***	-0.338***	-0.268*	-0.267*	-0.275***	-0.304***
	(-5.42)	(-4.61)	(-5.43)	(-4.78)	(-1.79)	(-1.73)	(-5.47)	(-4.42)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [Low TFP]		1.766***		1.878***		1.016***		1.768***
		(11.37)		(11.36)		(5.70)		(11.52)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [High TFP]		1.459***		1.540***		0.749***		1.465***
		(10.38)		(10.20)		(4.06)		(10.89)
Observations	826217	826217	738657	738657	86656	86656	842057	842057
Number of firms	183521	183521	166907	166907	16466	16466	185377	185377
Dep. var. avg;p50 (in %)	0.8;-3.5	0.8;-3.5	0.2;-4.3	0.2;-4.3	5.7;0	5.7;0	0.8;-3.5	0.8;-3.5
Panel B TFP cutoff : p33-p66								
$D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}$	-0.381***	-0.432***	-0.403***	-0.475***	-0.362*	-0.358*	-0.364***	-0.418***
	(-5.67)	(-4.81)	(-5.49)	(-4.87)	(-1.77)	(-1.69)	(-5.26)	(-4.51)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [Low TFP]		1.858***		1.997***		1.124***		1.914***
		(11.94)		(11.91)		(4.81)		(12.52)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [High TFP]		1.426***		1.522***		0.766***		1.496***
		(10.01)		(9.85)		(3.30)		(10.86)
Observations	564662	564662	505422	505422	58183	58183	574880	574881
Number of firms	138656	138656	125839	125839	12641	12641	139450	139450
Dep. var. avg;p50 (in %)	1.1;-3.3	1.1;-3.3	0.5;-4	0.5;-4	5.6;0	5.6;0	1;-3.2	1;-3.2
Panel C TFP cutoff : p25-p75								
$D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}$	-0.454***	-0.516***	-0.487***	-0.580***	-0.340	-0.290	-0.420***	-0.484***
	(-5.25)	(-4.49)	(-5.25)	(-4.68)	(-1.30)	(-1.09)	(-5.05)	(-4.14)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [Low TFP]		1.983***		2.150***		1.072***		1.974***
		(11.51)		(11.56)		(4.00)		(11.79)
⋄ $\mathrm{CF_{c,MAt,t\text{-}2}}$ [High TFP]		1.467***		1.570***		0.782***		1.490***
		(9.63)		(9.55)		(2.74)		(10.38)
Observations	401762	401762	359306	359306	41274	41274	410587	410588
Number of firms	104075	104075	94301	94301	9566	9566	104646	104646
Dep. var. avg;p50 (in %)	1.2;-3.1	1.2;-3.1	0.7;-3.7	0.7;-3.7	5.6;0	5.6;0	1.1;-3	1.1;-3
Firm $\mathrm{Controls_{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Macro $\mathrm{Controls_{c,t\text{-}1}}$	no	**yes**	no	**yes**	no	**yes**	no	**yes**
Country-Year FE	yes	**no**	yes	**no**	yes	**no**	yes	**no**
Other FE: i, s×t, c×s	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Delta\ln(y_{i,t})=\alpha+\beta\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$, and its variant Eq.(3) that replaces $\alpha_{c,t}$ with a vector of macro controls MC. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of financial debt of firm i in year t. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median (p50) log-TFP in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-year and size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year fixed effects. Odd-numbered columns include country-year fixed effects while even-numbered columns include a set of macro controls MC evaluated at t, $t-1$ and $t-2$. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Overall, our initial results suggest that at times of capital inflows, credit along the intensive margin goes to everyone, small and large firms (still, as expected with a higher sensitivity for small firms), and for both low and high TFP firms. Interestingly however, credit tends to go relatively more towards the least productive ones, and in nontrivial amount, especially when the comparison focuses on the tails of the TFP distribution within industries. This negative differential could simply be a reflection of the on-average higher credit demand from low TFP firms at times of inflows, but our fixed effect structure and firm controls should reasonably control for these differences in credit needs across firms.[50] More likely, these results may suggest that a rise in loanable funds incentivize banks to expand their scope of activity to the more marginal firms. Low TFP firms might face in normal times tighter credit constraints and thus a higher shadow value of additional funding when constraints get slacker. Alternatively, these firms might be on average riskier, in which case this negative selection may reflect banks' increased risk appetite in times of abundant liquidity and low risk premia following inflows of foreign capital. Section 5 will disentangle the possible explanations behind our results, but as a preview and in a nutshell, they appear to be most consistent with this last rationale, suggesting a risk-taking channel of capital inflows. But beforehand, we will extend our analysis on both the intensive and extensive margins of lending.

4.2 Intensive and Extensive Margins Adjustments

Our previous results use log growth rates of financial debt as our dependent variable, which are by construction left censored and undefined for firms moving from zero leverage to positive debt, nor from positive to zero debt. Hence, so far, our analysis has remained silent about debt adjustments on the extensive margin, that is, the contributions driven by firms' *entry* (into the credit market, i.e., begin to hold debt) and *exit* (from the credit market, i.e., do not hold debt any more). To get a more comprehensive view, we now consider two alternative dependent variables, introduced in Section 3.3.3, that accommodate changes in credit along both the intensive and extensive margins, with the DHS mid-point growth rate and the first difference of financial debt scaled by lagged total assets.

[50] We believe the presence of firm controls and a host of fixed effects help tease out the identification of supply-driven effects induced by capital inflows. In particular, industry-year dummies will absorb the impact of changes in credit demand for the four-digit sector that our firms operate in, thus assuming firms in the same narrowly defined sector have equal credit demand at a given time. Unreported results confirm as well the robustness to the inclusion of interacted country-industry-year fixed effects, which assume that loan demand changes equally for all firms within the same country-industry-year.

We first apply these two new dependent variables to the same previous sample conditional on firms having non-zero outstanding debt that accounts for the intensive margin alone, for the sake of comparability across samples and measures. Table 3 reports these results in the first four columns. Notwithstanding a different treatment of outliers, results based on the DHS growth rate (panel A) are very similar to the ones conducted using log-growth rates—not surprisingly given the second order approximation for small changes. On a different scale, absolute debt changes in terms of a firm's lagged total assets (panel B) lead to similar qualitative estimates. In economic terms, all else being equal, our estimates from column (2) on SME firms indicate that a 5 percentage points cumulative increase in debt inflows in country c (equivalent to the sample standard deviation) raises the proportion of credit in terms of total assets in ex-ante low TFP firms by 0.280 percentage point higher than in high productive firms within the same industry (which represents 25.4% of the mean change in the SME subsample, of 1.1% annually). It is worth noting that the negative differential effect within large firms is slightly more precisely estimated with the dependent variable defined as the scaled first-difference in debt (panel B), and of a roughly similar magnitude as the coefficient within SMEs firms—although in economic terms, the estimated differential effect of column (3), assuming a one standard deviation in capital inflows, represents 12.36% of the mean change in the large firms subsample, of 1.9% annually.

We next identify whether the intensive margin effects discussed thus far are complemented by extensive margin effects, too. Table 3 presents in the last four columns the results on both the intensive and extensive margins for the larger sample populated with the additional observations on entry into and exit from credit markets.[51] Across specifications (panels A-B) and samples (columns 5-8), the interaction coefficients are generally more pronounced, both in magnitude and in statistical terms, once we take account of both continuing credit flows to firms already indebted, and the information gain on new credit flows and credit flow disruptions at the extensive margin. For instance, when the outcome variable is computed using the DHS growth rate, the negative differential coefficient within the SME sub-sample moves from -0.279 (t-stat -5.25) at the intensive margin alone to -0.498 (t-stat -6.97) once the extensive margin is included.[52]

[51] Extensive changes for the full sample of firms account for 16.6% of all observations.

[52] Consistent with the results at the intensive margin only, Table C.2 in the Appendix shows for the estimation at both margins of lending that the negative differential effect becomes larger in magnitude as we move away from the median cutoff towards the tails of the TFP distribution.

Table 3. Firm's Debt Growth and Capital Inflows, Intensive and Extensive Margin Changes

Margin Changes:	**Intensive only**				**Intensive + Extensive** with {entry,exit} $\in$ Extensive			
Firm Samples:	All (1)	SMEs (2)	Large (3)	All (pool) (4)	All (5)	SMEs (6)	Large (7)	All (pool) (8)
Panel A Dep. var.: $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,MAt,t-2}}$	-0.263*** (-5.27)	-0.279*** (-5.25)	-0.294* (-1.96)	-0.269*** (-5.47)	-0.459*** (-6.80)	-0.498*** (-6.97)	-0.407** (-2.04)	-0.469*** (-6.99)
Observations	826217	738657	86656	842057	1022273	918248	103278	1040524
% Extensive changes	0%	0%	0%	0%	16.6%	16.8%	14.2%	16.5%
Number of firms	183521	166907	16466	185377	222376	202965	19296	224430
Dep. var. avg;p50 (in %)	-0.2;-3.5	-0.7;-4.3	4.3;0	-0.2;-3.5	-1.6;-4	-2;-4.7	1.5;0	-1.6;-4
Panel B Dep. var.: $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,MAt,t-2}}$	-0.053*** (-6.17)	-0.056*** (-6.05)	-0.047** (-1.99)	-0.049*** (-5.49)	-0.063*** (-7.38)	-0.065*** (-7.22)	-0.057*** (-2.62)	-0.058*** (-6.76)
Observations	826217	738657	86656	842057	1022273	918248	103278	1040524
% Extensive changes	0%	0%	0%	0%	16.6%	16.8%	14.2%	16.5%
Number of firms	183521	166907	16466	185377	222376	202965	19296	224430
Dep. var. avg;p50 (in %)	1.2;-0.5	1.1;-0.6	1.9;0	1.2;-0.5	1.4;-0.3	1.3;-0.4	1.7;0	1.3;-0.3
Firm $\text{Controls}_{\text{i,t-1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Macro $\text{Controls}_{\text{c,t-1}}$	no	no	no	no	no	no	no	no
Fixed Effects: i,$s\times t$,$c\times t$,$c\times s$	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi=\alpha+\beta\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. The dependent variable Ψ is computed in Panel A as the DHS mid-point growth rate in the financial debt y of firm i in year t, while in Panel B as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that is equal to 1 if a firm is in the high TFP bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and, except for columns (4 and 8), at the size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1

We further examine for the subsamples of SMEs and large firms to which extent entries (flow of loans to new borrowers) or exits (flow lost due to borrowers exiting) alone drive the contribution of the extensive margin effects. To this end, Table C.3 in the Appendix simply re-estimates the outcome variable at the joint intensive and extensive margins by successively excluding firm's debt flows at exit and at entry from the estimation sample. Results show that adding only exit observations to the intensive changes (columns 3 and 6) causes the interaction coefficients to drop by almost half relative to the specifications including all intensive and extensive changes (columns 1 and 4); conversely, the coefficients are barely unchanged or magnified when the sample is composed of intensive plus entry observations only (columns 2 and 5). This implies that the negative differential effects on the extensive margin are mostly driven by the relatively larger extension of credit to new low TFP firms, rather than the relatively smaller loan termination of high TFP firms.

Overall, our results suggest that following capital inflows not only the least ex-ante productive firms (SMEs and large firms) that were already indebted experience a larger increase in their relative amount of loans than their more productive industry peers, but also the proportion of firms entering the market and/or—as it is hard to disentangle the two—the net change in credit obtained when entering, is relatively higher among low TFP firms.

For the sake of comparison of results across samples and outcome measures, we have not considered the firms' observations where financial debt is equal to zero in both t and $t-1$, as the construction of the DHS mid-point growth rate would prescribed. To avoid losing relevant information on entrants, Table C.4 in the Appendix report the results where we set the corresponding debt change equal to zero whenever both y_t and y_{t-1} are zero. Clearly, including those zero change observations affect most coefficients dramatically. On one hand, we indeed expect the large proportion of added zeros (around 36% of observations) to attenuate all estimated coefficients, including the interaction terms, towards 0. On the other hand, those zero debt flows on the extensive margin are not randomly distributed; and the relative proportion of these zero records between low and high TFP firms would impact our interaction term of interest.[53] Reassuringly, even after accounting for this non-random distribution of zero debt changes, our qualitative conclusions in Table C.4 remain unchanged. The differential effect of capital inflows is still highly statistically significant, albeit smaller in magnitude partly due to the "mechanical" increase in the number of zero changes in the dependent variable. In economic terms, for instance, estimates from column (1) in panel B on SME firms indicate that, all else being equal, a 5 percentage points cumulative increase in a country's debt inflows raises the proportion of credit in terms of total assets in ex-ante low TFP firms by 0.17 percentage point higher than in high TFP firms within the same industry (which represents 21.2% of the mean change in the SME sub-sample, of 0.8% annually).

Incidentally, we supplement this evidence by estimating the extensive margin alone—as best as we can measure it—namely the probability of a firm gaining access to credit. We are interested in whether capital flows lead to greater financial inclusion for SMEs, and

[53] The more skewed the occurrence of these zero changes towards low TFP firms on average, the smaller would be the estimated differential between the two. In our sample, zero debt changes are roughly evenly distributed across low/high TFP firms (on average the relative proportion is 0.95).

if so, whether it is at the expense of a disproportionate access for low TFP firms relative to their more productive industry peers. To the extent that adjustments on the extensive margin depends on the net change in both the number (i.e., headcount) of new borrowers, and in their average loan (i.e., credit flows), we wish to isolate whether capital inflows lead banks to expand their loan portfolios by adding relatively more low TFP borrowers and omit the previously captured dimension on the extension in loan volumes to new entrants. The dependent variable is now defined as a dummy Z that equals 1 if a firm moves from zero financial leverage to a positive one, and 0 if it stays unlevered from $t-1$ to t.[54]

Table C.5 in the Appendix reports the results for the subsample of SMEs for different variants of estimation.[55] Column (1) shows that low productive SMEs are more likely to gain access to credit markets when aggregate credit constraints are eased, although the negative differential effect is imprecisely estimated (t-stat -1.38). In column (2), we require each firm that enters the regression to have at least four annual observations, which reduces sample size but helps clearing out some of the noise in estimating the firm-specific effects. Our interaction term is now more precisely estimated, albeit not strongly (t-stat -1.78). The analysis so far included as a control group of entrants the observations corresponding to non-switching debt-free firms that stay always unlevered, which inevitably drags all effects towards zero. As we focus on within-firm dynamics, we repeat in columns (3-4) the same analysis but this time we only consider the switching zero leverage firms—as would a fixed effects (conditional) logit do by dropping from the estimation firms reporting time-invariant access to credit. Based on estimates of column (4), in the sample of SME firms with at least 4 years of data, a 1 percentage point cumulative increase in debt inflows in a country, ceteris paribus, raises the probability of entry to credit markets of initially low TFP firms by 17.9 percentage points more than of high TFP firms within the same industry (t-stat -2.20), which represents 79% of the mean probability of switching to positive debt.[56]

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[54] We run the following binary choice specification, assuming a linear probability model (LPM): $Pr(Z{=}1){=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\big){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, with Z equals 1 if $y_{i,t-1}{=}0$ and $y_{i,t}{>}0$, and 0 if $y_{i,t-1}{=}y_{i,t}{=}0$. We include the same controls and fixed effects as in Eq.(1). Instead of using non-linear models, we opt for an LPM in order to include firm fixed effects and estimates marginal effects. As only a negligible fraction of predicted probabilities fall outside the unit interval, the LPM is expected to be unbiased and consistent, or largely so (Horrace and Oaxaca, 2006).

[55] Firm controls have generally the expected signs; the likelihood of a firm switching to positive debt rises in years when its size, pledgeable assets, or growth opportunities are above their firm averages.

[56] Following Strebulaev and Yang (2013), we also consider the probability of firms exiting "almost-zero" leverage, where Z equals 1 if a firm moves above 2% of financial leverage in t and 0 if it stays with almost-zero leverage. Results reported in the right end of Appendix Table C.5 are consistent.

Taken together, results indicate that within SMEs, low TFP firms tend to experience after capital inflows a larger probability to access credit markets as well as a larger committed credit at entry. It is worth to mention that with the firm as the unit of analysis, variability due to extensive margin adjustments within a firm is much lower than compared to the importance of those adjustments within a bank portfolio at a more disaggregated level in bank-firm-year data. Still, the contribution of extensive margin adjustments is not negligible even at this level of aggregation, especially at entry, and broadly points to the same direction as the intensive margin effects, that the least productive firms tend to benefit relatively more from the higher supply of credit following surges in capital flows.

5. Why Is Credit Flowing to the Least Productive Firms?

Why would banks at time of abundant liquidity allocate relatively more credit to these low TFP firms? Are these firms ex-ante more (or less) financially constrained than their high productive peers, and/or are they relatively riskier? Moreover, is credit flowing systematically more to the least productive firms, or are there some nuances along some collateral or risk dimensions? While we do not have information on credit terms such as loan interest rates and collateral requirements nor on the strength of the bank-borrower relationship, which would typically be available in loan-level dataset, we can nonetheless infer from firms' characteristics the extent to which collateral and risk metrics matter in explaining our results. We first outline several potential explanations, some more likely than others, and starting in Section 5.2, we bring more evidence suggesting that this negative selection might capture risk considerations from banks pursuing higher returns.

5.1 Two Potential Explanations

In our empirical setup, it seems unlikely, as previously argued, that our results would be entirely driven by systematic differences in credit needs across low and high TFP firms. Rather, we can think of two potential supply-based explanations.

First, our results could capture the fact that capital inflows tend to benefit relatively more firms that face ex-ante tighter financial constraints, and those also happen to be the least productive ones. One could hypothesize that while banks in normal times are mostly satisfying the credit needs of large firms counting as their main customers, at times of inflows of liquidity, banks expand their scope of activity towards the credit-constrained SME segment, wherein information asymmetries are generally more acute (Rajan, 1992; Berger et al., 2001). Because banks are inexperienced in serving those customers and due to costly screening, or alternatively because banks might lack incentive to screen borrowers and become more laxist at times of abundant liquidity, their lending could be unintentionally skewed on average towards the least productive firms, that eventually face in normal times relatively more binding credit constraints.[57] Thus, on the assumption that low TFP firms have on average a higher shadow value of additional funding, our results might reflect the positive spillover effect of capital inflows on domestic credit markets by relieving firms' credit constraints.

However, it is unclear that low TFP firms are indeed the most financially constrained. It is possible that they have a low TFP precisely because of their limited access to credit and lack of internal funds to make productivity-enhancing investments.[58] On the other hand, high TFP firms, while facing less stringent credit constraints for a given level of capital, might not have enough internal funds to sustain their optimal level of capital, which makes them more likely to hit their borrowing constraint and more sensitive to external finance. Specifically, absent any capital adjustment costs or risk in capital accumulation, tighter credit constraints (e.g. in the form of higher collateral requirements) introduce dispersion in the marginal revenue product of capital (MRPK) across firms (Hsieh and Klenow, 2009; Larrain and Stumpner, 2017). To the extent that MRPK is higher in high TFP firms, these firms are hungry for more capital but are unable to invest as much as desired, thus theory would predict they face greater credit constraints (Barlevy, 2003; Catherine et al., 2022; Liu and Wang, 2014; Lenzu and Manaresi, 2019).[59] Hence, we would expect credit growth in more productive firms to show a greater sensitivity to the easing of aggregate credit constraints, which is at odds with our results where the least productive firms are getting the most credit.

Second and alternatively, our results could reflect the fact that following capital inflows, or more generally at times of booms, banks take increased risk in their side activities by

[57] As opposed to a lack of *incentive*, a lack of *capacity* to screen induced by higher information asymmetries is somehow less compatible with our findings. The latter would imply that the differential is much stronger on average within SMEs than within large firms, which is not clearly the case in our sample, and we would expect information asymmetries to primarily influence lending along the extensive margin for unlevered firms, unlike our results that also account for the intensive margin.

[58] Credit-constrained firms may accumulate fewer intangible assets since they are less pledgeable as collateral (e.g. Almeida and Campello, 2007; Garcia-Macia, 2017; Duval et al., 2020) and may switch investment away from long-term R&D expenses due to short-run liquidity risks (Aghion et al., 2010).

[59] For instance, Li (2019) show that firms with higher MRPK are more likely to be financially constrained as they display a greater sensitivity of investment to their cash flows.

extending credit to more marginal, riskier borrowers. From the banks' point of view, there is a priori no incentive for them to allocate loans mainly to the least productive firms per se, but this negative selection could rather be the (unintended) consequence of their intentional increased risk appetite and hunt for yield in times of abundant liquidity and low risk premia. Recent studies have highlighted the transmission of the Global Financial Cycle (GFC) and international financial flows to the local credit market, and reveal that cross-border (banking) flows are often associated with higher aggregate bank loan volumes and lower borrowing costs (Baskaya et al., 2017; di Giovanni et al., 2021). Yet, akin to lax monetary policy, foreign capital inflows, by increasing the quantity and reducing the price of loanable funds, may also have implications on the dynamics of bank risk-taking. This second possible explanation is supported by empirical and theoretical ground in the related literature.

Ample empirical evidence vindicates the presence of a monetary policy ‘‘risk-taking channel’’.[60] For instance, Jiménez et al. (2014) find that low interest rates in Spain, due to the higher collateral values and the search for yield, induce banks to soften their lending standards and grant more loans to risky borrowers. Few empirical papers, however, analyze the effects of capital inflows on the risk-taking behavior of banks. The literature is still recent and without broad consensus. In Dinger and te Kaat (2020) for the euro area, capital flows are associated with a deterioration of bank asset quality aggravated by bank agency issues, while Karolyi et al. (2018) find, on the other hand, some improvements due to the positive effect induced on competition and monitoring. These two bank-level studies are however unable to further explore the impact on the composition of banks' loan portfolios, that is what type of borrowers benefit disproportionately more. te Kaat (2021) takes a first step in this direction using firm-level data on large firms and shows that debt flows raise overproportionally the credit growth rates of low-profitable firms and the riskier ones, although the evidence is mainly drawn from within-firm dynamics. Bedayo et al. (2020) exploit loan applications from Spain and document that loan origination time, as a measure of bank screening, is shorter when the VIX is lower (in booms) especially for riskier borrowers; bank incentives (capital and competition), capacity constraints, and information frictions are key mechanisms driving their results. In contrast, relying on loan-level data for Italy,

[60] Lax monetary policy tends to be associated with higher riskiness of bank lending: see, for example, loan-level studies by Dell'Ariccia et al. (2017) for the U.S., Jiménez et al. (2014) for Spain, Morais et al. (2019) on Mexico and the spillovers of foreign monetary policy, and Ioannidou et al. (2015) for Bolivia; as well as cross-country bank-level evidence (e.g. Altunbas et al., 2014; Maddaloni and Peydró, 2011) or bank-firm data as in Acharya et al. (2019).

Cingano and Hassan (2020) find that banks more exposed to capital inflows expand lending relatively more to the safer firms, in particular the high TFP–high collateralized (and good credit score) firms.

From a theoretical perspective, several papers emphasize the link between the rise in loanable funds and interest rate reductions with the riskiness of bank credit allocation (Keeton, 1999; Dell'Ariccia and Marquez, 2006; Acharya and Naqvi, 2012; Martinez-Miera and Repullo, 2017; Coimbra and Rey, 2021; Bolton et al., 2021, among others). For example, Coimbra and Rey (2021) show that in times of low interest rates,[61] a further decrease in funding costs encourages the most leveraged risk-taking institutions, because of looser value-at-risk constraints, to accept lower credit-worthiness of borrowers and increase further their leverage, pricing out of the market less risk-taking intermediaries. In Martinez-Miera and Repullo (2017)'s model, a global savings glut—and the ensuing capital inflows—, by reducing domestic interest rates, lowers loan rate spreads (and compresses intermediation interest margins), which provides an incentive for banks to reduce monitoring and ultimately to shift their loan portfolios towards lower quality lending in return for higher yields.

While it is unfeasible to rule all other possibilities, we now explore to what extent the latter two explanations may influence our findings. To this end, and as a first step, we put the productivity dimension aside, and allow for heterogeneity in the effects of capital inflows across firms with different initial risk or collateral availability. We then examine whether in our sample low and high productive firms differ in any meaningful way in terms of these two attributes. Next, we introduce back the TFP dimension and evaluate if, conditional on firm collateral or risk heterogeneity alone, any nuances emerge and whether the TFP dimension continues to matter. Finally, to test if each of these dimensions has an independent effect and to further isolate one channel, we include all three collectively.

Under the first rationale, we would expect the credit growth of credit-constrained firms, i.e., those with initially less collateral, to be more responsive to capital inflows. In the hypothetical case where the availability of collateral is positively related to TFP in the cross-section of firms, we should observe our main interaction term $CF \times D^{TFP}$ to lose statistical significance when further conditioning on firms heterogeneity in pledgeable assets. Collectively, this would suggest that capital inflows help alleviate the burden of prevailing financial constraints borne disproportionally by low-productivity firms. Conversely, according

[61] As the authors suggest, similar effects can be expected after large capital inflows.

to the second rationale, if more loans to low TFP firms is a sign of increased bank risk-taking, we would expect capital inflows to induce a credit allocation titled towards the riskiest firms, and that low TFP firms in the sample are on average riskier. Ultimately, the heterogeneity in firms' productivity should lose its relevance after accounting for differences in firm risk. As will be seen thereafter, our results appear to be most consistent with this second interpretation, wherein high risk–high collateral firms fare substantially better when capital flows in, suggesting the presence of a risk-taking channel of capital inflows.

5.2 Patterns of Credit Allocation Across Other Firm Characteristics

We start by exploring the differential effect of capital inflows for other firm characteristics. First, we assess the riskiness of credit allocation, that is the extent to which riskier firms receive new credit relative to safer firms following capital inflows. We leave aside our interaction of interest and introduce several firm risk proxies in their interactions with foreign capital flows, namely: the Altman's Z score as a summary measure of corporate fragility and risk of bankruptcy, the debt overhang ratio also referred to as debt service capacity in the corporate finance literature (Kalemli-Özcan et al., 2019), and the cash-flow ratio—lower values for these 3 proxies imply a higher risk—as well as the total leverage ratio.[62]

Table 4 presents the results.[63] We find that capital inflows disproportionately raise the credit growth of ex-ante riskier firms relative to their less financially vulnerable industry peers. This holds for all four risk indicators (columns 1-4) and the differential effects are more pronounced in the tails of the risk metrics' distributions (i.e., moving from panels A to C). These results are consistent with prior empirical works and theoretical arguments that banks, in the wake of capital inflows, increase their lending especially so to risky borrowers.

Secondly, we examine the relevance of borrowers' financial constraints. We introduce a dummy based on firm's collateral ratio interacted with capital inflows. Credit constraints

[62] Specifically, we use the four variables Altman's Z''-Score model as it is intended for privately held firms across all sectors (Altman, 1983; Altman et al., 2017). The debt overhang ratio is an indicator of the extent of profits relative to the size of accumulated debts and is computed as the three-year moving average of past earnings (EBIT) divided by total liabilities (Borensztein and Ye, 2021; Brandao-Marques et al., 2019). Note that while the interest coverage ratio better capture the drag on finances stemming from debt payments, its coverage is however relatively poor within our sample. The cash-flow ratio is the ratio of changes in cash holdings scaled by total assets, and the leverage ratio is computed as the sum of current and non-current liabilities divided by total assets. Similar to TFP, these firm-level risk proxies are defined ex-ante and in the form of dummies.

[63] Tables C.7 and C.8 in the Appendix report the results when the intensive and extensive margin changes are jointly estimated and when we include or not firms that stay unlevered in a specific year.

Table 4. Debt Growth and Capital Inflows, Other Firm Characteristics

Margin Changes: **Intensive only** *Dependent variable*: $\Delta\ln(y_{i,t})$	**Risk**				**Financial Constraints**	
Firm-level Proxies:	**Altman's Z Score** (1)	**Debt Overhang** (2)	**Cash-Flow Ratio** (3)	**Leverage Ratio** (4)	**Collateral Ratio** (5)	**Cash Ratio** (6)
Panel A: proxy cutoff p50						
$D^{Proxy}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.587***	-0.344***	-0.290***	0.249***	0.288***	-0.368***
	(-11.81)	(-7.06)	(-5.33)	(4.76)	(6.32)	(-7.04)
Observations	808395	840077	739804	862829	870246	742401
Number of firms	181739	186407	172943	187945	187443	172875
Panel B: proxy cutoff p33-p66						
$D^{Proxy}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.872***	-0.616***	-0.446***	0.592***	0.400***	-0.506***
	(-12.41)	(-8.89)	(-5.97)	(7.68)	(6.24)	(-7.44)
Observations	511196	522480	487984	573381	598044	492924
Number of firms	131824	135666	130967	140852	140771	130519
Panel C: proxy cutoff p25-p75						
$D^{Proxy}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-1.193***	-0.839***	-0.587***	0.835***	0.343***	-0.659***
	(-12.32)	(-8.33)	(-6.12)	(8.17)	(4.30)	(-7.21)
Observations	339526	344126	328754	400129	435367	342467
Number of firms	94607	97851	96548	104673	107498	97645
Firm $\mathrm{Controls}_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Delta\ln(y_{i,t}){=}\alpha{+}\beta\big(D^{Proxy}_{i,t-1}{\times}CF_{c,MA,t,t-2}\big){+}\gamma D^{Proxy}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of outstanding financial debt of firm i in year t, thus focusing only on the intensive margin of credit growth. D^{Proxy} is a time-varying dummy that is equal to 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median (p50) in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-year-size class (SME, large) level. *Proxy* is defined in the table. The Altman's Z-Score is based on the four variables Altman's Z''-Score model (Altman, 1983; Altman et al., 2017) (the lower score, the more financial vulnerability), the debt overhang ratio is computed as the three-year moving average of past EBIT divided by total assets, the cash-flow ratio is the ratio of cash flows scaled by total assets, the leverage ratio is computed as total debt divided by total assets, the collateral ratio is proxied by the ratio of tangible assets over total assets, and the cash ratio is measured as cash and cash equivalents divided by total assets. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, and growth opportunities. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

should be less stringent, on average, for firms with high collateral, more tangible assets.[64] If the financial accelerator is operative (Bernanke et al., 1999), the supply of credit to financially constrained firms should be more cyclically sensitive. We would thus expect a greater sensitivity of debt growth to capital inflows for firms with ex-ante lower collateral. On the other hand, di Giovanni et al. (2021) show that collateral-based borrowing constraints

[64] While we do not observe collateral requirements, we assume that tangible assets are either pledged as collateral or, if not, are potentially attachable as collateral by the bank.

do not necessarily relax during capital flow surges, firms' "hard" collateral constraints do not change since capital that serves as collateral does not get over-valued when capital flows into the banking sector. Firms are instead able to borrow at lower rates on average. Thus, if lending is indeed severely constrained by the availability of collateral, and capital inflows work mostly through the "interest rate channel" highlighted in di Giovanni et al. (2021) as opposed to the balance sheet channel, we should expect firms with more pledgeable assets to disproportionately benefit from the easing of credit conditions.

Column (5) of Table 4 shows that the effect of capital inflows on firm's debt growth is significantly stronger for firms with high preexisting collateral, which goes against our first explanation laid out in the previous section. It appears capital inflows do not necessarily relax banks' demand for collateral, as emphasized by di Giovanni et al. (2021). This is also consistent with the size-dependent borrowing constraint documented in Gopinath et al. (2017). This finding is unaltered when grouping firms based on the cash ratio measure (see column 6); following capital inflows, debt grows disproportionately more for the least constrained firms with low cash reserves—assuming firms hold cash as a precautionary motive against future credit constraints (Keynes, 1936; Opler et al., 1999; Erel et al., 2015).

Hence, we find that capital inflows not only benefit disproportionately more the low TFP firms, but the credit allocation is also skewed towards the riskier firms and the firms with higher collateral availability. This finding is surprising at first sight, but is nonetheless in line with the empirical literature on collateral. While most of the theoretical research on collateral argue that safer firms tend to pledge collateral to signal their quality (e.g. Bester, 1985), many empirical studies find however a positive relationship between collateral and risk premium (e.g., Berger and Udell, 1990, 1995; Jiménez et al., 2006), suggesting that banks would be able to sort the borrowers from information they have on their quality, the so-called observed-risk hypothesis. Thus, as a result of their higher risk-taking, banks nonetheless compensate their risky allocation by hedges, either by charging riskier borrowers with higher loan rates and/or requiring higher collateral to protect against future potential losses.

At this point, it is instructive to take a closer look at the differences between low and high TFP firms in our analysis sample. As shown in Table C.6 in the Appendix, low TFP firms are on average riskier and hold more collateral than high TFP firms, the difference between these means is significant at the 1 percent level and economically meaningful, and more pronounced as we raise the TFP cut-off. Furthermore, Figure C.I in the Appendix shows important disparities in the empirical bivariate densities of low TFP versus high TFP firms as a function of firm's collateral and risk. The relative density distribution plots, depicted on the right-hand side, reveal that high risk/high collateral attributes (right-lower quadrant) are over-represented among firms with low level of TFP (deeper red), while low risk/low collateral characteristics are relatively more prevalent among high TFP firms (deeper blue). Consequently, in light of results in Table 4, these large discrepancies in collateral and risk attributes across firms of different productivities may account for our finding that banks expand their lending relatively more to ex-ante low TFP firms following capital inflows.

5.3 TFP–Collateral and TFP–Risk Dimensions

We now turn to a more rigorous analysis of the role of collateral and risk considerations together with the productivity dimension in the implications of capital inflows on banks' credit allocation. We seek to determine whether the larger accumulation of debt induced by capital inflows towards low TFP firms is state invariant, or if conversely, there are some nuances along the collateral or risk dimensions. Further, we aim to evaluate if conditional on firm collateral or risk heterogeneity alone, the TFP dimension continues to matter.

Accordingly, we split firms into four groups according to the TFP and collateral dimensions on the one hand and by the TFP and risk dimensions on the other hand, and thus allow the effect of capital inflows on debt growth to vary for each group. In constructing these four categories, we hold the cutoff for the TFP dimension at the median (i,e., H• > median), while we apply different thresholds for the second dimension (•H or •L); moving away from the median allows for a more relevant assessment of the heterogeneity in firms' risk or collateral availability.[65] Table 5 presents results for the TFP–collateral dimensions in columns (1-3) and for the TFP–risk as proxied by the Altman's Z score in columns (4-6).[66] To ease interpretation, we report in the bottom of the table the relative ranking of the four groups as implied by the estimated differential effects, as well as their absolute coefficients.

[65]For example, the Altman's Z score model introduce two cutoffs to distinguish firms, and the "grey area" usually hosts an overlapping population frequency of both failed and non-failed firms. Recall from Figure C.I that differences in terms of collateral and risk attributes in firm proportions across high and low TFP groups are especially marked when moving away from the plots' central region. Also, Table 4 finds stronger differential effects across these other firm proxies for higher cutoffs.

[66]The full results at the intensive margin for all firm-level proxies in their interaction with TFP are presented in Table C.9 in the Appendix. Table C.10 reports the results for the joint estimation of the intensive and extensive margins. Broadly speaking, results are consistent across all tables.

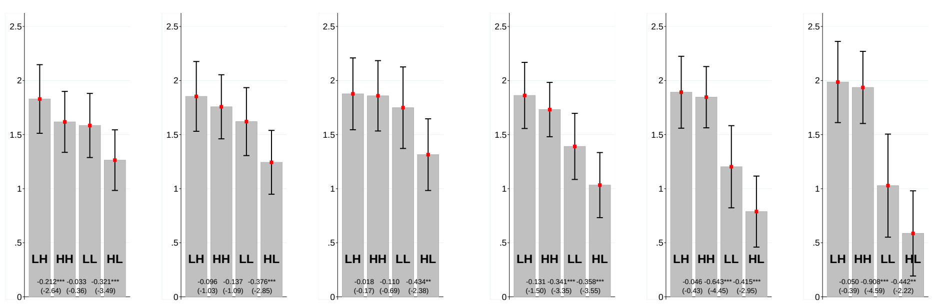
Table 5. Debt Growth and Capital Inflows, TFP–Collateral and TFP–Risk

Margin Changes: **Intensive only**
Dependent variable: $\Delta\ln(y_{i,t})$

Dimension 1: TFP (H•: High TFP, p50 cutoff);
Dimension 2:

	Collateral Ratio (•H : High Collateral)			**Altman's Z Score** (•H : High Risk)		
Cut-off for Dimension 2	p50 (1)	p33-p66 (2)	p25-p75 (3)	p50 (4)	p33-p66 (5)	p25-p75 (6)
$CF_{c,MAt,t\text{-}2}$ [HH-LH]	-0.15^{**}	-0.05	0.05	-0.05	0.06	0.06
	(-2.50)	(-0.75)	(0.62)	(-0.77)	(0.71)	(0.52)
$CF_{c,MAt,t\text{-}2}$ [LL-LH]	-0.17^{**}	-0.15	-0.05	-0.39^{***}	-0.61^{***}	-0.90^{***}
	(-2.33)	(-1.40)	(-0.37)	(-4.89)	(-5.30)	(-5.47)
$CF_{c,MAt,t\text{-}2}$ [HL-LH]	-0.52^{***}	-0.56^{***}	-0.46^{***}	-0.76^{***}	-1.04^{***}	-1.35^{***}
	(-7.59)	(-6.48)	(-4.22)	(-10.35)	(-10.32)	(-9.71)
$CF_{c,MAt,t\text{-}2}$ [HH-LL]	0.02	0.10	0.10	0.34^{***}	0.67^{***}	0.96^{***}
	(0.28)	(0.87)	(0.71)	(4.12)	(5.59)	(5.62)
$CF_{c,MAt,t\text{-}2}$ [HH-HL]	0.37^{***}	0.50^{***}	0.51^{***}	0.72^{***}	1.10^{***}	1.40^{***}
	(5.68)	(5.70)	(4.50)	((10.05)	((11.35)	((10.24)
$CF_{c,MAt,t\text{-}2}$ [LL-HL]	0.35^{***}	0.41^{***}	0.42^{***}	0.37^{***}	0.43^{***}	0.44^{**}
	(4.09)	(3.38)	(2.59)	(4.02)	(3.39)	(2.41)
Test H0: •H=•L	18.45^{***}	16.94^{***}	10.22^{***}	61.890^{***}	74.520^{***}	63.390^{***}
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Test H0: H•=L•	10.31^{***}	5.90^{***}	3.57^{**}	8.17^{***}	6.27^{***}	3.13^{**}
(p-value)	(0.000)	(0.000)	(0.030)	(0.000)	(0.000)	(0.040)
Observations	743527	505024	366154	694094	431904	284584
Number of firms	173929	127876	96703	168472	118505	83487
Relative Ranking$^{[\%obs.]}$	$LH^{[32\%]}$	$LH^{[37\%]}$	$HH^{[28\%]}$	$LH^{[32\%]}$	$HH^{[27\%]}$	$HH^{[28\%]}$
	$HH^{[27\%]}$	$HH^{[29\%]}$	$LH^{[39\%]}$	$HH^{[29\%]}$	$LH^{[33\%]}$	$LH^{[36\%]}$
	$LL^{[15\%]}$	$LL^{[11\%]}$	$LL^{[10\%]}$	$LL^{[15\%]}$	$LL^{[15\%]}$	$LL^{[13\%]}$
	$HL^{[26\%]}$	$HL^{[23\%]}$	$HL^{[23\%]}$	$HL^{[24\%]}$	$HL^{[26\%]}$	$HL^{[24\%]}$

Absolute coefficients (y-axis) based on complementary regressions w/o country-year FE but including macro controls, 95% confidence intervals



Note: This table reports the results of estimating $\Delta\ln(y_{i,t})=\alpha+\beta\left(D^{TFP}_{i,t-1}\times D^{Proxy}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma_1 D^{TFP}_{i,t-1}+\gamma_2 D^{Proxy}_{i,t-1}+\delta_1\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\delta_2\left(D^{Proxy}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of outstanding financial debt of firm i in year t, thus focusing on debt changes at the intensive margin only. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year-size class (SME, large) level. Similarly defined, the dummy D^{Proxy} uses as cut-offs either the median, the p33-p66, or the p25-p75 thresholds. *Proxy*, i.e. dimension 2, is defined in the table. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities, and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Applying the same decomposition of firms along the TFP–collateral dimensions, Cingano and Hassan (2020) examine also how the impact of capital inflows on bank credit supply varies across groups. Interestingly, they argue that in frictionless markets in which risk-averse banks seek to achieve an efficient risk-return trade-off, an increase in loanable funds should be channeled disproportionately towards the high TFP–high collateral firms (HH) while credit should not increase, or to a limited extent, for low TFP–low collateral borrowers (LL), and the other categories should be capped from this range.[67]

Unsurprisingly, the pecking order in our study deviates in some aspects from what classic risk-return trade-off would predict. First, Table 5 reveals that firms with high collateral or high risk (•H) are in general benefiting the most from the easing of credit conditions. Interestingly, conditional on having high collateral or on being of high risk, high TFP firms (HH) do benefit sometimes as much as low TFP firms (LH). This brings some important nuances to our main findings in that capital inflows do not benefit systematically more the low productivity firms; the allocation of credit is not state invariant.

Secondly, and in marked contrast, results show that conditional on being of high productivity, lending after capital inflows increases systematically the least for low collateral or low risk firms (HL group).[68] For instance, using estimates in column (2), a 5 percentage points cumulative increase in debt inflows raises the annual credit growth rates of low TFP–high collateral firms (LH) firms by 2.8 percentage points more than of high TFP–low collateral firms (HL) within the same industry, all things equal. As regards the risk dimension, the implied differential between the low TFP–high risk (LH) and high TFP–low risk (HL) groups reaches a difference of 5.2 percentage points, based on estimates in column (5).

Thirdly, we observe with the joint-significance test (H0: •H=•L, i.e. $LH{=}LL$ and $HH{=}HL$) that lending, similar to Cingano and Hassan (2020), is severely constrained by the availability of collateral, but especially so to high productive firms (HH-HL). Furthermore, it appears that the increase in lending is heavily biased towards high risk borrowers, as indicated also by the significantly large F-statistics. These two observations are consistent with the results we presented in Table 4. The significance of TFP, on the other hand, fades

[67] For the case of Italy, the authors find that banks exposed to financial flows increased credit supply disproportionally to high TFP–high collateral firms, and that collateral availability seems a necessary condition for being granted more credit.

[68] The differences of these HL firms with respect to the other three categories of firms are all large and highly statistically significant, hold for the various collateral or risk cutoffs, and are robust across all five risk and financial constraints proxies as reported in Table C.9 in the Appendix.

in importance once we account for differences in firms' risk or collateral as indicated by the joint significance test (H0: H•=L•); especially in comparison to the other two dimensions, and as we move the cutoff further to the distribution tails of collateral/risk. The productivity dimension continues nonetheless to have an influence on our estimates. Some puzzles indeed remain, as can be gauged from the difference LL-HL, that is conditional on having low collateral, the increase in lending to low TFP firms is significantly larger than for high TFP firms, which may be due to differences in firms' riskiness. Moreover, there is no significant difference between high TFP firms with high collateral (HH) and low TFP firms with low collateral (LL). Finally, conditional on having low risk, we still find a puzzling difference between high and low TFP firms (LL-HL), which in turn may be due to collateral constraints.

One would not expect these last observations if collateral constraints alone or differences in firms' risk alone were the sole mechanisms behind our core results that the least productive firms are getting the most credit. In line with our conjecture, collateral and risk are often positively associated, but the relationship is not 1-to-1 and while instructive, this exercise introduced these two dimensions consecutively, which will be relaxed in the next section.

5.4 Accounting Simultaneously for Collateral and Risk Dimensions

Lastly, Table 6 explores the patterns of credit supply according to firms' ex-ante TFP, and accounting concurrently for both the degree of collateral availability and firms' riskiness. In a nutshell, the table suggests that the relation between capital inflows and the within-industry credit allocation towards low productivity firms is driven by their higher relative riskiness and to a less extent, their higher endowment in pledgeable assets.

More specifically, for each of the three threshold definitions to construct the collateral and risk dummies, all specifications in Table 6 are run on the same sample with non-missing observations for the three firm dummies—productivity, collateral, and risk. In doing so, we can better assess how the coefficient on our main interaction term $CF \times D^{TFP}$ changes when horseracing capital inflows in its interaction with firms' collateral and firms' riskiness consecutively (columns 4-6 and 7-9, respectively), and simultaneously (columns 10-12).

Like in the previous exercise, columns (3-6) and columns (7-9) of Table 6 confirm the relevance to account for the collateral and risk dimensions; they both enter the model with positive and statistically significant coefficients.[69] Delving deeper, columns (10-12) introduce

[69] While results in columns (3-9) of Table 6 bear resemblance with the tests of joint significance reported

the three interaction terms simultaneously. The differential effects of capital inflows between high and low risky firms is highly statistically significant and of sizable magnitude, while the one induced by collateral availability somewhat appears redundant.[70] Importantly, when compared to the baseline estimates, the magnitude and statistical significance of our main interaction coefficient on $CF \times D^{TFP}$ is much lower once we account jointly for differences in firms' riskiness and collateral. Using estimates in column (12), which are based on quartile cutoffs for the collateral and risk dummies, the difference in the effect of capital inflows between high and low TFP firms declines substantially in statistical significance, more than half in magnitude (from a coefficient of -0.48 to -0.21), and is around seven times smaller than the coefficient on $CF \times D^{Risk}$. Likewise, the heterogeneity in firms' productivity is no longer significant when measuring risk by the debt overhang ratio (Appendix Table C.11).

Finally, the last columns (13-15) introduce concurrently the three dummies in their interaction with capital inflows and allows for all the lower level interaction terms. These specifications essentially split the set of firms into eight groups along the productivity, collateral and risk dimensions. For exposition clarity, we report only the tests of joint significance for the three firm characteristics, and below these tests, we re-estimate these specifications splitting firms into four aggregate groups.[71] As opposed to the risk dimension, the TFP dimension, as indicated by the F-statistics on the null hypothesis that H••=L••, is only marginally, or no longer, statistically significant. Further, our results are clearly driven by the considerable difference in the effect of capital inflows on debt growth between LHH firms (low TFP–high collateral–high risk) and HLL (high TFP–low collateral–low risk) firms, which represent together almost 45% of observations. Consequently, these results reinforce the perception that the documented credit allocation titled towards low TFP firms following surges in capital flows is driven to a large extent by the marked differential responses between low and high risk firms. This is consistent with a risk-taking channel of capital inflows that ultimately cause the differential credit growth patterns we observe on firms that differ in their productivity.

in Table 5, they do not include the triple interaction term $CF \times D^{TFP} \times D^{Proxy}$, and as such, impose that $\beta_{\{CF \times D^{TFP}\}}$=HL-LL=HH-LH and $\beta_{\{CF \times D^{Proxy}\}}$=HH-HL=LH-LL.

[70] As underscored earlier, there is a strong positive association between collateral and risk. Note that the collateral dimension remains statistically significant when measuring risk by the debt overhang ratio (see Appendix Table C.11), although its magnitude is comparatively small.

[71] As follows: LHH (low TFP–high collateral–high risk) versus HLL (high TFP–low collateral–low risk), capturing together almost 45% of observations, and regrouping the rest of firms into two categories, low TFP *Lrest* (i.e., LLH, LHL, LLL) and high TFP *Hrest* (i.e., HLH, HHL,HHH).

Table 6. Debt Growth and Capital Inflows, TFP–Collateral–Risk (Altman's Z Score)

Margin Changes: **Intensive only** *Dependent variable*: $\Delta \ln(y_{i,t})$	**Risk proxy: Altman's Z Score**														
	TFP			**TFP–Collateral** (•H : High Collateral)			**TFP–Risk** (•H : High Risk)			**TFP–Collateral–Risk** (quadruple interaction=0)			**TFP–Collateral–Risk** (8 categories)		
Cut-off for Collateral and Risk dummies	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$D^{TFP}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$	-0.28***	-0.36***	-0.48***	-0.23***	-0.25***	-0.35***	-0.22***	-0.22**	-0.20	-0.20***	-0.18**	-0.21			
	(-4.92)	(-3.99)	(-3.67)	(-4.04)	(-2.73)	(-2.61)	(-3.84)	(-2.37)	(-1.53)	(-3.44)	(-1.97)	(-1.57)			
$D^{COL}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$				0.27***	0.51***	0.55***				0.15***	0.22*	-0.06			
				(4.78)	(4.54)	(2.98)				(2.60)	(1.82)	(-0.30)			
$D^{RISK}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$							0.52***	0.88***	1.48***	0.49***	0.81***	1.50***			
							(9.40)	(8.18)	(7.98)	(8.41)	(6.86)	(7.29)			
Test H0: H••=L•• [TFP]													**3.89*** **	**2.26***	**0.73**
(p-value)													**(0.000)**	**(0.060)**	**(0.570)**
Test H0: •H•= •L• [COL]													**2.70****	**1.13**	**0.50**
(p-value)													**(0.030)**	**(0.340)**	**(0.730)**
Test H0: ••H=••L [RISK]													**19.850*** **	**13.180*** **	**14.210*** **
(p-value)													**(0.000)**	**(0.000)**	**(0.000)**
$CF_{c,MAt,t\text{-}2}$ [Hrest-LHH]													-0.22***	-0.32***	-0.40***
													(-3.36)	(-3.09)	(-2.70)
$CF_{c,MAt,t\text{-}2}$[Hrest - Lrest]													-0.01	0.17	0.44*
													(-0.19)	(1.20)	(1.86)
$CF_{c,MAt,t\text{-}2}$[Hrest - HLL]													0.57***	0.80***	1.19***
													(6.67)	(4.85)	(4.55)
$CF_{c,MAt,t\text{-}2}$ [Lrest-LHH]													-0.21***	-0.49***	-0.84***
													(-2.79)	(-3.56)	(-3.48)
$CF_{c,MAt,t\text{-}2}$[Lrest - HLL]													0.59***	0.64***	0.75**
													(5.96)	(3.47)	(2.57)
$CF_{c,MAt,t\text{-}2}$ [HLL-LHH]													-0.80***	-1.13***	-1.59***
													(-8.75)	(-6.86)	(-6.12)
Observations	599004	258410	131091	599004	258410	131091	599004	258410	131091	599004	258410	131091	599004	258410	131091
Number of firms	151498	75717	40810	151498	75717	40810	151498	75717	40810	151498	75717	40810	151498	75717	40810
Within R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03
Relative Ranking[%obs.]	L[47%] H[53%]	L[50%] H[50%]	L[53%] H[47%]	LH[33%] HH[28%] LL[14%] HL[25%]	LH[39%] HH[29%] LL[10%] HL[22%]	LH[44%] HH[28%] LL[9%] HL[20%]	LH[32%] HH[29%] LL[15%] HL[24%]	LH[36%] HH[28%] LL[13%] HL[22%]	LH[42%] HH[29%] LL[11%] HL[19%]				LHH[25%] Lrest[22%] Hrest[38%] HLL[14%]	LHH[31%] Hrest[36%] Lrest[18%] HLL[14%]	LHH[37%] Hrest[34%] Lrest[15%] HLL[13%]

Note: Details on the regressions ran in this table are given in the main text. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high TFP bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. D^{COL} and D^{RISK} are time-varying dummies that equal 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median, terciles or quartiles in the collateral ratio or the Altman's Z score (times -1) at the country-industry-size-year level. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities, and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

5.5 Main Takeaways

Section 5 investigated why debt inflows are associated with relatively higher credit growth rates of ex-ante low TFP firms within an industry. We conjectured that there are a priori no reasons for banks to allocate credit overproportionally to low TFP firms per se, but productivity would rather stand for other firm dimensions, i.e., other considerations entering the banks' optimal risk-return profile. We find that credit does not systematically flow to low TFP firms, in that there exists some nuances along the firms' collateral and risk heterogeneity. Further, we show that debt inflows induce a relatively larger lending towards firms with initially high collateral, which stands in contrast to the possibility that inflows would have helped alleviate the burden of credit constraints borne disproportionally by low TFP firms. This is instead consistent with di Giovanni et al. (2021)'s results that debt inflows do not necessarily relax banks' demand for collateral and is broadly in line with the size-dependent credit constraints observed in Gopinath et al. (2017) and Cingano and Hassan (2020).

Nevertheless, as reflected in the empirical literature on collateral that finds riskier firms to pledge collateral more often and thus supporting an observed-risk hypothesis, our results suggest that risk considerations from banks pursing higher returns contribute ultimately to our baseline findings. Specifically, capital inflows seem to induce banks to expand relatively more their credit supply to low TFP firms, because these firms are relatively riskier. It is clearly reflected in the large differential responses between low TFP–high risk firms versus high TFP–low risk firms. We thus provide further evidence to the nascent empirical studies on the risk-taking channel of capital inflows (te Kaat, 2021; Dinger and te Kaat, 2020; Bedayo et al., 2020; Cantú et al., 2022). These results fit naturally with the theoretical insights on the link between the rise in loanable funds and interest rate reductions, and incentives for banks to search for yield (e.g. Martinez-Miera and Repullo, 2017; Coimbra and Rey, 2021).

Our collective findings thereby imply a connection between two recent literatures on the effects of capital inflows, that both identify banks' credit allocation across firms as the main mediating channel. The literature studying the impact of foreign capital on the misallocation of resources do map financial frictions to misallocation, but hardly consider the financial sector risk-taking as a transmission channel. In the literature on the risk-taking channel of capital inflows, a risky credit allocation may cause financial stability threats, but may also bear some unintended effects in driving credit to the non-productive part of the economy.

6. Further Analysis and Robustness

We now push the analysis further and provide four refinements to our benchmark results. First, we discuss whether our findings can be interpreted as evidence of an inefficient credit allocation, and in doing so, explore the within-firm sensitivity of future TFP growth to the use of external finance and if credit is directed at better use in ex-ante low TFP firms. Second, we take into consideration the direction of non-resident flows, distinguishing positive from negative inflows. Third, we contrast our results on emerging economies from a sample of more advanced countries, while mitigating representativeness issues across- and within-countries. Fourth, we look at heterogeneity within SMEs and across macro industries. Lastly, we conduct an extensive set of robustness checks with, for instance, alternative measures of firm productivity, and various capital inflows variables and their supply-side components.

6.1 A Credit "Misallocation"?

Prima facie, our results seem consistent with the idea that international financial flows contribute to an "inefficient allocation" of credit towards the least productive firms within an industry. In Hsieh and Klenow (2009)'s misallocation framework, a firm with a higher level of revenue TFP relative to its industry average, despite offering higher factor remunerations, is unable to accumulate assets and hire labor it would need to expand, and thus remain inefficiently small (Calligaris et al., 2018). Conversely, although they offer lower remunerations, low revenue TFP firms are inefficiently large. Accordingly, the mere finding that credit at times of capital inflows is disproportionately allocated towards firms that are inefficiently over-resourced lends support to a credit misallocation.

Naturally one could argue, however, that low TFP firms might face ex-ante relatively more credit constraints that limit their expenditures in innovative projects.[72] Recent micro-based studies show a significant negative relationship between financial frictions and productivity growth at the firm-level, through the impact that such frictions have on the ability to sustain investments in human capital, IT adoption or more radical innovation.[73] By alleviating the burden of credit constraints, capital inflows might give the opportunity for low TFP

[72] However, as we discussed in the previous section, it is unclear that low productive firms are indeed the most financially constrained. Moreover, our results suggest that capital inflows induce a relatively larger lending towards firms with more collateral, that also happen to be relatively riskier.

[73] A non-exhaustive list includes Manaresi and Pierri (2019), Caggese (2019), Levine and Warusawitharana (2021), and Lenzu et al. (2021).

firms to obtain the additional credit needed to fund investments in productivity-enhancing activities, and eventually enable them catch up to the technological frontiers.

To explore this argument, and as a further step to assess whether our findings support a misallocation of credit, we estimate the within-firm sensitivity of future TFP growth to the use of external finance. If the least productive firms are likely to be the most financially constrained, we would expect them to experience the largest TFP gain. In order to account for the persistence in the dynamics of TFP growth rates, we follow the dynamic panel approach in Levine and Warusawitharana (2021), formally:

$$\Delta TFP_{i,t+1}{=}\rho_1 \Delta TFP_{i,t}{+}\rho_2 \Delta TFP_{i,t-1}{+}\psi \Delta Debt_{i,t}{+}\theta_l W^l_{i,t}{+}\alpha_i{+}\alpha_{c,t}{+}\epsilon_{i,t+1} \tag{4}$$

where firms' TFP growth from year t to $t{+}1$ ($\Delta TFP_{i,t+1}$, with TFP in log terms) is regressed on its own lagged terms (up to two lags as dictated by specification tests) and on the firms' financial debt change in year t ($\Delta Debt_{i,t}$), measured either as the log-difference of financial debt or as the first difference of debt scaled by lagged assets to accommodate adjustments on both the intensive and extensive margins.[74] The specification includes firm fixed effects and a set of controls W_t including firm size, growth opportunities, physical investment (i.e., growth in fixed assets), the industry's median TFP growth, and country-year dummies.

Because panel data fixed-effects estimators are biased in the presence of lagged-dependent variables (Holtz-Eakin et al., 1988), we employ the Difference GMM estimator of Arellano and Bond (1991). This estimator first-differences the observation equation Eq. (4) to eliminate α_i, thus focusing only on within-firm variation. As instruments for the endogenous lagged dependent variables in the differenced equation, we use for parsimony only the second and third lag of the dependent variable while all other right-hand side variables are treated as exogenous and included directly in the instrument set.[75] Table 7 shows our results.

[74] Ideally, we would like to focus on firm-level credit supply shocks induced by capital inflows, but such identification is not available in our context. We nonetheless also perform unreported regressions with a measure of residual debt changes as in Bertrand et al. (2007) by taking out the part that can be explained by changes in observable firm characteristics, and find consistent results. Of note, we do not expect capital inflows to affect the within-firm sensitivity of future TFP growth to debt changes.

[75] To assess the validity of our instruments, we report two standard diagnostic tests. The first is the Hansen J test of overidentification restrictions with a null hypothesis that the instruments are jointly exogenous. The second test (AR) is based on the serial correlation in the first-differenced residuals, and has a null hypothesis of no autocorrelation. Our estimations require the absence of second-order serial correlation. Some of our regressions, however, arguably fail to satisfy these two specification tests, i.e. the corresponding p-values are uncomfortably close to zero. As is usual for Difference GMM estimations (Blundell et al., 2001), these two tests have a tendency to over-reject their respective null hypotheses in heterogeneous samples with very large cross-sections relative to the time dimension (e.g. Blundell et al., 2001; Benito, 2003; Ferrando et al., 2017;

Table 7. Sensitivity of TFP growth to Debt Change, Ex-ante High versus Low TFP Firms

Dependent variable: Δ $\mathrm{TFP_{i,t+1}}$								
ΔDebt defined as:	**Panel A: Intensive only** $\triangle\ln(Debt_{i,t})$				**Panel B: Intensive + Extensive** $(\Delta Debt_{i,t})/(TotalAssets_{i,t-1})$			
Firm Samples:	All firms (1)	All firms (2)	Ex-ante High TFP (3)	Ex-ante Low TFP (4)	All firms (5)	All firms (6)	Ex-ante High TFP (7)	Ex-ante Low TFP (8)
Δ $\mathrm{TFP_{i,t}}$	-0.171*** (-49.50)	-0.171*** (-49.60)	-0.140*** (-29.98)	-0.200*** (-37.15)	-0.167*** (-52.90)	-0.166*** (-52.61)	-0.136*** (-31.82)	-0.193*** (-39.17)
Δ $\mathrm{TFP_{i,t-1}}$	-0.058*** (-21.69)	-0.058*** (-21.69)	-0.046*** (-12.62)	-0.059*** (-14.16)	-0.057*** (-23.37)	-0.057*** (-23.35)	-0.047*** (-13.97)	-0.055*** (-14.35)
Debt $\mathrm{Chg_{i,t}}$	0.021*** (24.74)				0.146*** (28.19)			
◇ Debt $\mathrm{Chg_{i,t}}^{+}$		0.002 (1.14)	**0.004*** **(1.75)**	**-0.001** **(-0.29)**		0.084*** (9.57)	**0.113***** **(9.71)**	**0.046***** **(3.51)**
◇ Debt $\mathrm{Chg_{i,t}}^{-}$		0.042*** (20.70)	**0.042***** **(15.03)**	**0.041***** **(14.21)**		0.276*** (17.82)	**0.263***** **(12.23)**	**0.289***** **(13.02)**
◇ Debt $\mathrm{Chg_{i,t}}^{+vs.-}$		-0.040*** (-14.03)	-0.038*** (-9.78)	-0.042*** (-10.07)		-0.193*** (-10.13)	-0.151*** (-5.80)	-0.243*** (-8.72)
Firm $\mathrm{Size_{i,t}}$	-0.151*** (-40.14)	-0.152*** (-40.50)	-0.166*** (-32.54)	-0.145*** (-25.44)	-0.154*** (-44.37)	-0.153*** (-44.21)	-0.170*** (-35.51)	-0.141*** (-27.89)
Growth $\mathrm{opp._{i,t}}$	0.405*** (8.94)	0.400*** (8.85)	0.446*** (7.33)	0.335*** (5.02)	0.405*** (9.81)	0.403*** (9.77)	0.471*** (8.19)	0.313*** (5.42)
$\mathrm{Investment_{i,t}}$	0.016*** (22.19)	0.018*** (23.56)	0.018*** (18.59)	0.019*** (15.13)	0.013*** (16.39)	0.014*** (16.72)	0.014*** (12.22)	0.014*** (14.50)
Δ Industry $\mathrm{TFP_{s,t}}$	-0.155*** (-8.62)	-0.153*** (-8.54)	-0.188*** (-7.50)	-0.109*** (-4.26)	-0.161*** (-9.75)	-0.161*** (-9.72)	-0.194*** (-8.36)	-0.115*** (-4.89)
Country-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	353491	353491	195385	158106	426201	426201	234806	191395
% Extensive changes	0%	0%	0%	0%	11.3%	11.3%	11.1%	11.6%
Number of firms	111133	111133	63958	58513	132088	132088	76095	70011
AR test, order 1 (p-val)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
AR test, order 2 (p-val)	0.164	0.156	0.723	0.019	0.043	0.038	0.090	0.144
Hansen J-Test (p-val)	0.009	0.012	0.081	0.152	0.001	0.001	0.008	0.161

Note: This table reports the results from an Arellano-Bond dynamic panel data regression (Difference GMM) using the first two lags of the dependent variable as regressors. The dependent variable is $\Delta TFP_{i,t+1}$. Results in columns (1) and (5) are based on estimating Eq.(4), where firm's financial debt change ($\Delta Debt_{i,t}$) is measured either as the log-difference of debt (panel A) or as the first difference of debt scaled by lagged assets to accommodate both intensive and extensive margins' adjustments (panel B). Other columns augment Eq.(4) with an interaction of $\Delta Debt_{i,t}$ with an indicator variable differentiating positive versus negative debt changes. Columns (3-4) and (7-8) further split the sample of firms based on the productivity dummy D^{TFP} that distinguishes high from low TFP firms within the same country-industry-size-year strata. The last three lines report the p-values of a test for first and second order auto-correlation in the first-differenced residuals, and for the Hansen J-test of overidentifying restrictions. Country-year fixed effects were included but not reported. The t-statistics reported in parentheses are based on robust standard errors adjusted for clustering at the firm-level. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Meriküll and Rõõm, 2014; Gebauer et al., 2018). In this context, we repeat our estimations for 20 stratified random samples, each comprising 10% of the original sample whilst preserving its distribution characteristics. Reassuringly, out of these 20 random samples, the median p-value for AR(2) tests is 0.37 and 0.36 for the Hansen J test.

In line with the evidence in Levine and Warusawitharana (2021) for a sample of three advanced countries, we find that, on average, firms that receive new credit exhibit higher productivity growth, and that much of the initial increase in TFP persists. This relationship is however found to be strongly concave in Manaresi and Pierri (2019). Hence, we re-estimate Eq. (4) with an indicator differentiating positive from negative debt changes, and find that a contraction in firms' credit has indeed comparatively much larger effects on future TFP growth. More interesting still are the results which decompose this average effect by firms' initial TFP level, wherein firms are split into two sub-samples using our usual productivity dummy D^{TFP}. Both type of firms show a statistically significant negative coefficient when credit dries up. By contrast, when exposed to an increase in credit, firms with high initial TFP levels show by far the largest relative TFP acceleration.[76]

Thus, if anything, our results seem to indicate that credit is not relatively at better use in ex-ante low productive firms and does not necessarily lead to a catch up. Along these lines, the confluence of all the results presented is consistent with the overall message that capital inflows in our sample of emerging economies induce a misallocation of credit towards the least productive firms within an industry. Extending credit to these firms means less funding to more productive and inefficiently under-resourced firms that could use additional funds in a more productive way, or the least could attract more capital and labor inputs to grow.

6.2 Does the Direction of Non-Resident Flows Matter?

We now ask whether the observed negative differential effect of capital inflows occurs principally when there is an increase in loanable funds as non-residents increase their financial exposures to the domestic economy, or when foreign funding dries up as non-residents liquidate their holdings, or in both type of episodes? Furthermore, we recognize that gross positive and negative capital inflows may not have symmetric effects on the domestic allocation of credit across firms. This decomposition is especially relevant as all countries in our sample experienced large and positive gross debt inflows before 2008, but with the onset of the global financial crisis, debt inflows turned into negative territory as foreigners withdrew funds from the region, a negative trend that continued for certain countries until 2017 (see Appendix

[76] Results are broadly similar if we use instead a triple interaction term $\Delta Debt_{i,t} \times D^{\Delta^+ Debt} \times D^{TFP}$. Alternatively, we have also considered a simple regression following Bertrand et al. (2007) where the cumulative TFP growth from t to $t+2$ is regressed on debt change in t, as follows: $TFP_{i,t+2} - TFP_{i,t} = \psi \Delta Debt_{i,t} + \theta_l X^l_{i,t} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t+2}$. Results in Appendix Table C.12 are again consistent.

Figure B.I).[77] Our results below suggest that both positive and negative capital inflows are found on average to hinder the ability of allocating credit to the most productive firms.

Along this vein, we further augment our interaction of interest with an outflow dummy D^{OUT} that equals one when debt inflows are negative (outflows in the sense that non-residents are reducing their lending).[78] We thus allow the differential effect β to differ between positive and negative inflows episodes. Table 8 presents the results for various timing of CF as well as the effects of capital inflows for both the relative (columns 1-3) and absolute (columns 4-7) growth rates of debt across low and high TFP firms. We find that larger positive debt inflows CF^{IN} are associated with a higher flow of credit to less productive firms, a result that echoes the evidence in Gopinath et al. (2017) which documents an increase in capital misallocation in Southern European countries in the pre-crisis period due to badly allocated positive capital inflows. The differential effect is especially strong when inflows are measured as the moving average of contemporaneous and the past two years (column 3).

Interestingly, the impact on the allocation of credit is not limited to capital inflows surges, but extends to times of negative debt inflows when non-residents shift their funds outside the domestic private sector. For convenience, we multiply negative inflows by -1, so that higher CF^{OUT} in Table 8 is interpreted as an increase in capital outflows, i.e., foreign investors are liquidating their claims to a greater extent. Symmetrically, a negative liquidity shock arising from a departure of foreign capital appears to affect negatively firms' flow of financial debt, especially so for ex-ante high productive firms. For instance, based on column (3) estimates at the intensive margin and all things equal, a 1 percentage point cumulative debt outflows in country c decreases the credit growth rates of high TFP firms by 0.42 percentage point more than of low TFP firms within the same industry. Whilst the direction of the differential effects is symmetric and statistically significant for both types of episode, in that low TFP firms in general experience a larger increase in credit during positive inflows and face a milder reduction at times of outflows, the magnitude of the differentials across firms are stronger in negative episodes. The effects of outflows occur also somewhat faster, as seen by the coefficient on CF^{OUT-IN} for shorter lags, but the differentials lessen at longer lags as low TFP firms become eventually less shielded from the contraction of credit supply.

[77] Figure B.II in the Appendix shows the proportion of the final sample observations broken down by countries and the direction of capital inflows.

[78] Our study focuses on capital inflows, i.e., changes in the financial liabilities L of a domestic country vis-à-vis non-residents. While usually denominated "gross inflows", they are themselves net items ($CF{=}L^{+}{-}L^{-}$), and can be negative (positive) for non-resident decrease (increase) in lending.

Table 8. Firm's Debt Growth and Capital Inflows, Positive versus Negative Inflows

Country-year FE	yes			no		
CF timing K:	t	MAt,t-1	MAt,t-2	t	MAt,t-1	MAt,t-2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intensive Margin						
Dep. var.: $\triangle$ ln(Financial Debt)						
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT\text{ - }IN}}$	-0.244**	-0.338**	-0.031	-0.166	-0.274	0.204
	(-2.16)	(-2.36)	(-0.18)	(-1.14)	(-1.00)	(0.51)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{IN}}$	-0.296***	-0.344***	-0.390***	-0.354***	-0.341***	-0.421***
	(-4.59)	(-4.95)	(-5.05)	(-5.13)	(-4.53)	(-5.13)
◇ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [Low TFP]				0.952***	1.191***	0.693***
				(11.75)	(11.26)	(6.49)
◇ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [High TFP]				0.598***	0.850***	0.272**
				(7.58)	(7.42)	(2.29)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT}}$	-0.540***	-0.682***	-0.422***	-0.521***	-0.615**	-0.218
	(-5.43)	(-5.37)	(-2.64)	(-4.07)	(-2.36)	(-0.55)
◇ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [Low TFP]				-0.577***	-2.190***	-5.580***
				(-3.09)	(-4.68)	(-7.59)
◇ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [High TFP]				-1.098***	-2.805***	-5.798***
				(-6.34)	(-8.10)	(-10.53)
Observations	826217	826217	826217	826217	826217	826217
% Extensive changes	0%	0%	0%	0%	0%	0%
Number of firms	183521	183521	183521	183521	183521	183521
Within Adj. R^2	0.024	0.024	0.024	0.028	0.031	0.035
Panel B: Intensive + Extensive Margins						
Dep. var.: $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$						
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT\text{ - }IN}}$	-0.458***	-0.218	0.089	-0.336*	0.037	0.317
	(-2.77)	(-1.09)	(0.37)	(-1.91)	(0.15)	(0.94)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{IN}}$	-0.406***	-0.466***	-0.504***	-0.430***	-0.503***	-0.546***
	(-4.80)	(-5.08)	(-5.05)	(-4.97)	(-5.35)	(-5.35)
◇ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [Low TFP]				0.302***	1.075***	0.630***
				(2.83)	(8.82)	(4.63)
◇ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [High TFP]				-0.128	0.573***	0.084
				(-1.30)	(4.19)	(0.56)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT}}$	-0.864***	-0.684***	-0.415*	-0.766***	-0.465**	-0.229
	(-5.77)	(-3.67)	(-1.80)	(-4.85)	(-1.97)	(-0.70)
◇ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [Low TFP]				0.512***	-0.676*	-3.405***
				(2.76)	(-1.90)	(-6.51)
◇ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [High TFP]				-0.254	-1.141***	-3.635***
				(-1.52)	(-3.85)	(-8.58)
Observations	1022273	1022273	1022273	1022273	1022273	1022273
% Extensive changes	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%
Number of firms	222376	222376	222376	222376	222376	222376
Within Adj. R^2	0.017	0.017	0.017	0.018	0.019	0.020

Table 8. (*continued*)

Country-year FE	yes			no		
CF timing K:	t	MAt,t-1	MAt,t-2	t	MAt,t-1	MAt,t-2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Intensive + Extensive Margins						
Dep. var.: $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$						
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT\text{ - }IN}}$	-0.027	-0.042*	-0.005	-0.026	-0.041	-0.006
	(-1.53)	(-1.70)	(-0.17)	(-1.35)	(-1.33)	(-0.15)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{IN}}$	-0.057***	-0.062***	-0.076***	-0.058***	-0.062***	-0.079***
	(-5.73)	(-5.88)	(-6.32)	(-5.77)	(-5.63)	(-6.39)
⋄ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [Low TFP]				0.150***	0.240***	0.216***
				(12.22)	(14.99)	(12.86)
⋄ $\mathrm{CF_{c,K}}^{\mathrm{IN}}$ [High TFP]				0.092***	0.178***	0.137***
				(7.86)	(10.43)	(7.51)
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,K}}^{\mathbf{OUT}}$	-0.083***	-0.104***	-0.081***	-0.084***	-0.104***	-0.085**
	(-5.55)	(-4.79)	(-3.01)	(-5.18)	(-3.69)	(-2.25)
⋄ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [Low TFP]				0.013	-0.128***	-0.401***
				(0.63)	(-2.84)	(-5.47)
⋄ $\mathrm{CF_{c,K}}^{\mathrm{OUT}}$ [High TFP]				-0.071***	-0.232***	-0.486***
				(-3.84)	(-6.80)	(-8.50)
Observations	1022273	1022273	1022273	1022273	1022273	1022273
% Extensive changes	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%
Number of firms	222376	222376	222376	222376	222376	222376
Within Adj. R^2	0.047	0.048	0.048	0.048	0.050	0.051
Firm $\mathrm{Controls_{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes
Macro $\mathrm{Controls_{c,t\text{-}1}}$	**no**	**no**	**no**	**yes**	**yes**	**yes**
Country-Year FE	**yes**	**yes**	**yes**	**no**	**no**	**no**
Other Fixed Effects: i, $s\times t$, $c\times s$	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\times D^{OUT}\right){+}\delta_1 D^{TFP}_{i,t-1}\times D^{OUT}{+}\delta_2 D^{TFP}_{i,t-1}{+}\gamma D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, and its variant that replace $\alpha_{c,t}$ with $MC^m_{c,t,t-2}$. Ψ is defined in each panel of the table. $y_{i,t}$ denotes the financial debt of firm i in year t. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year $t-q$ to year t (q=0,1,2). D^{OUT} denotes an outflow dummy which equals 1 when capital inflows are negative. We multiplied these negative inflows by -1, so that higher CF^{OUT} implies an increase in capital outflows, i.e., non-residents disinvest to a greater extent. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. Columns (1-3) are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects, while columns (4-6) include a set of macro controls instead of country-year dummies. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1

Hence, these results suggest the lack of so-called cleansing effects (Caballero and Hammour, 1994; Osotimehin and Pappadà, 2017) when credit conditions tighten. Instead, capital outflows may impart ‘‘scarring effects’’ (Ouyang, 2009), as banks appears to reduce their supply of credit more strongly for high productive firms when foreign funding dries up. One could expect that banks faced with scarce liquidity and subject to risk-sensitive capital requirements may decide to reallocate their loan portfolio towards firms deemed to be more credit-worthy, on the assumption that such companies would be able to service their debt. Conversely, financial pressure in times of capital outflows may create incentives for banks, especially the under-capitalized ones, to engage in forbearance lending (also referred to as zombie lending or evergreening). Because of the impact on their profitability and regulatory capital ratios, troubled banks might be willing to keep riskier borrowers afloat by rolling over their debt in order to avoid write-offs and the crystallizing of credit losses on their balance sheets (Keuschnigg and Kogler, 2020). This phenomenon of zombie lending is supported by ample evidence for Japan during the ‘‘lost decade’’ (e.g. Caballero et al., 2008; Peek and Rosengren, 2005), or for the Euro area during the Eurozone crisis (Acharya et al., 2019).[79] Our findings on negative capital inflows fall naturally under this perception as zombie firms are often lacking productivity. These results, could also reflect, in light of Section 5, increasing bank risk-taking at times of accommodative policies (Bittner et al., 2022).[80]

6.3 Contrasts From a Sample of Advanced Countries

The stronger the financial frictions emerging markets are subject to provides a natural starting point for exploring the domestic bank intermediation of capital inflows and whether credit is adequately channeled. But, the question arises to what extent this negative differential effect towards low TFP firms can be considered an emerging economies phenomenon? We now extend parts of our empirical analyses to a sample of 10 advanced European economies.[81] To draw meaningful comparisons between samples of advanced and emerging countries, we

[79] Schivardi et al. (2021) show that weakly capitalized banks in Italy during the Eurozone crisis were more likely to maintain credit lines (or slower to cut credit) to zombie firms at the expenses of healthy ones; confirming Andrews and Petroulakis (2019)'s results in 11 European countries. Iyer et al. (2014) and Farinha et al. (2019) offer diverging results based on Portuguese loan-level data.

[80] In the context of low-rate environment and the supporting policies, these capital outflows do not necessarily coincide with a rise in spreads, so bank profitability might still be under pressure which could incentivize them to cut to a less extent lending to the most marginal firms. Of note, we cannot fully rule out the possibility that our differential effect in period of capital outflows would be confounded by demand-side dynamics. This could be the case if, for example, high TFP firms have higher average net open foreign currency positions and as a result would be more adversely affected after a sudden stop. Also, if the timing of firms' borrowing is endogenous as in Mian and Santos (2018)'s study of the U.S. syndicate loan market, the stronger contraction in credit in high TFP firms could reflect their lower need of refinancing in distress periods, assuming they have a greater capacity to refinance their loans and extend their maturities when credit conditions are good—although this active liquidity management hypothesis seems unlikely within SMEs (Chodorow-Reich et al., 2021).

[81] Specifically, we include Austria, Belgium, Finland, France, Germany, Italy, Norway, Portugal, Spain and Sweden. Of note, firms in Denmark, Ireland, Iceland, the Netherlands, Switzerland, and the United Kingdom have limited data and are not included in this sample.

will further mitigate issues of sample's representativeness and unbalancedness. In a nutshell, we show that capital inflows in advanced countries are also associated with a higher flow of credit to less productive firms, yet this negative differential effect is (intuitively) significantly smaller, and more asymmetric depending on the direction of non-resident flows.

6.3.1 Baseline Comparisons

Results are summarized in Table 9, wherein we contrast for convenience the estimates from advanced countries (referred to as "*Adv10*") with our previous results on all firms from emerging economies (referred to as "*CEE12*"). Three key insights emerge from Table 9.

First, and similar to the emerging countries sample, foreign capital tend to induce relatively higher credit flows to low TFP firms. The interaction coefficient from our baseline specification reported in panel A is negative and statistically significant, mainly driven across SME firms within industries, and robust across our three measures of firms' debt changes.

Second, those differentials appear nonetheless substantially smaller in advanced economies. Estimates in column (10) indicate that a 7 percentage points cumulative increase in a country's debt inflows (equivalent to one standard deviation in the *Adv10* sample) raises the proportion of credit in terms of total assets in low TFP firms by 0.091 percentage point higher than their more productive industry peers, which is modest against a 0.8% average annual debt change. This contrasts with the non-trivial estimates found in our baseline analysis, which accords with the idea that capital inflows have greater implications for small open economies and credit market distortions have greater bite in less advanced banking sectors.

Third, and in contrast to the emerging countries sample, the negative differential effect in advanced countries, as it is evident from Panel B,[82] occurs principally when non-residents liquidate their holdings, albeit the magnitude appears again modest. This suggests that increases in loanable funds during positive inflows do not necessarily lead banks in advanced economies to favor more the least productive firms (or riskier firms as per Section 5),[83] but when foreign funding dries up, banks appear to curb lending more strongly for high TFP firms. This could be symptomatic of evergreening (see e.g. Schivardi et al., 2021), and/or a reflection of banks' search for yield in periods of supporting policies amid outflows episodes.

[82] As done previously, we augment $CF \times D^{TFP}$ with an outflow dummy, and multiply negative capital inflows by -1, so that higher CF^{OUT} implies non-residents disinvest to a greater extent.

[83] This result should be put into perspective with Gopinath et al. (2017)'s observation that MRPK dispersion has been relatively stable in Germany, France, and Norway in the 2000s, and with Cingano and Hassan (2020)'s findings that the boom of capital inflows in Italy favored firms with higher TFP.

Table 9. Contrasts Between European Emerging Countries (CEE12) versus European Advanced Countries (Adv10)

Margin Changes & Dependent variable	**Intensive Only** $\triangle \ln(y_{i,t})$				**Intensive + Extensive** $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$				**Intensive + Extensive** $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$			
Country sample:	**CEE12**	**Adv10**			**CEE12**	**Adv10**			**CEE12**	**Adv10**		
Firm Samples:	All	All	SME	Large	All	All	SME	Large	All	All	SME	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Benchmark												
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.276***	-0.034***	-0.038***	-0.035	-0.459***	-0.072***	-0.110***	-0.030	-0.063***	-0.013***	-0.017***	-0.004
	(-5.42)	(-2.70)	(-2.80)	(-1.29)	(-6.80)	(-3.86)	(-5.32)	(-0.83)	(-7.38)	(-5.86)	(-6.87)	(-0.97)
Panel B: Inflows vs. Outflows												
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}{}^{\mathbf{OUT\ -\ IN}}$	-0.031	-0.121***	-0.136***	-0.055	0.089	-0.243***	-0.270***	-0.182	-0.005	-0.025***	-0.027***	-0.028**
	(-0.18)	(-3.44)	(-3.62)	(-0.68)	(0.37)	(-4.47)	(-4.47)	(-1.62)	(-0.17)	(-3.47)	(-3.48)	(-2.21)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}{}^{\mathbf{IN}}$	-0.390***	-0.059***	-0.064***	-0.054	-0.504***	-0.011	-0.039	0.000	-0.076***	-0.004	-0.006*	0.000
	(-5.05)	(-3.02)	(-3.10)	(-1.27)	(-5.05)	(-0.36)	(-1.19)	(0.00)	(-6.32)	(-1.13)	(-1.79)	(-0.02)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}{}^{\mathbf{OUT}}$	-0.422***	-0.180***	-0.200***	-0.109	-0.415*	-0.254***	-0.310***	-0.182*	-0.081***	-0.028***	-0.033***	-0.028**
	(-2.64)	(-5.66)	(-5.88)	(-1.40)	(-1.80)	(-5.15)	(-5.74)	(-1.67)	(-3.01)	(-4.27)	(-4.64)	(-2.26)
Firm $\mathrm{Controls}_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	826217	5333437	4485898	847293	1022273	6306073	5362749	943118	1022273	6306073	5362749	943118
% Extensive changes	0%	0%	0%	0%	16.6%	13.8%	14.6%	9.2%	16.6%	13.8%	14.6%	9.2%
Number of firms	183521	1029599	886503	143049	222376	1173633	1016776	156824	222376	1173633	1016776	156824
Within Adj. R^2	0.024	0.018	0.019	0.014	0.017	0.012	0.013	0.010	0.048	0.036	0.038	0.029
Dep. var. avg;p50 (in %)	0.8;-3.5	-2.2;-6.3	-2.5;-6.8	-0.5;-3	-1.6;-4	-2.6;-6.4	-2.6;-6.9	-2.2;-3.3	1.4;-0.3	0.8;-0.7	0.8;-0.9	0.7;-0.2

Note: This table reports the results of estimating in panel A $\Psi{=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}\big){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$. Panel B further augments our interaction of interest with an outflow dummy D^{OUT} which is equal to one when capital inflows are negative (outflows in the sense that non-residents are reducing their lending). Results are shown for both the sample of 12 emerging European countries (referred to as CEE12) and the sample of 10 advanced European countries (referred to as Adv10). The dependent variable Ψ focuses on intensive margin changes only with the log-difference of a firm's financial debt, or by jointly estimating the intensive and extensive margin changes with the DHS mid-point growth rate or the first-difference of debt scaled by total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. In panel B, for convenience, we multiplied the negative inflows by -1, so that higher CF^{OUT} is interpreted as an increase in capital outflows, that is non-residents investors are liquidating their claims to a greater extent. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

6.3.2 Mitigating Issues of Sample Representativeness and Unbalancedness

One concern, however, is that data coverage varies a lot across countries and the samples we rely on are not necessarily representative of the whole population of firms within a country, which could hamper our comparisons across advanced versus emerging countries. Reassuringly, we show below that our conclusions are broadly upheld when based on weighted least squares (WLS) regressions that use different weighting schemes to alleviate part of these concerns. Table 10 reports the weighted results for the *CEE12* and *Adv10* groups.[84]

We first check whether our results are not primarily driven by a few countries due to cross-country differences in sample size.[85] To mitigate the unbalanced nature of the panel along the country and year dimensions, we weight observations by the inverse of the number of a country's observations in a given year as a share of all observations in that year (i.e., $w_{c,t}{=}N_t/N_{c,t}$), which gives an equal weight to each country-year.

Next, we apply a weighting scheme to ensure, as far as possible, within-country representativeness. Smaller and younger firms in the raw ORBIS data tend to be under-represented, and more so in some industries/countries than in others. Besides, the size of the original dataset is greatly reduced once measures of firms' flow of credit and TFP have been obtained. There is no assurance that the remaining samples of analysis can be regarded representative of the population of businesses across size classes, sectors, and countries.[86] To mitigate these concerns, we align our final samples with the distribution of the true firm population as reflected in the Structural Demographic Business Statistics (SDBS) collected by the OECD and Eurostat from national business registers. Following the procedure in Schwellnus and Arnold (2008) and Gal (2013),[87] re-sampling weights are applied using SDBS information on the number of employees and turnover in a country-industry-size class-year cell, which

[84] We focus on the specification that allow β to differ between positive and negative inflows episodes. Further, we restrict our attention to the samples that offer most coverage, i.e., when the intensive and extensive margin changes are jointly estimated. Similar results are obtained if we instead use our largest samples that include firms that stay unlevered in a specific year (see Appendix Table C.13).

[85] As described in Section 3.2, our final samples show a wide variation in the number of observations across countries, and across years within a country. Appendix Tables B.8-B.9 describe the advanced countries' samples, wherein 80% of the firm-year pairs are massed in France, Italy, and Spain.

[86] Following Kalemli-Özcan et al. (2015)'s guidelines, our sample put together data from several vintages to minimize survivorship bias, especially in small firms, and is restricted to European countries with relatively better coverage. While there might be less of a need of re-weighting, representativeness concerns still remain as our analysis is demanding in terms of data availability and quality.

[87] This method is frequently used in ORBIS-based studies, see e.g. Andrews and Cingano (2014), Dall'Olio et al. (2013), Bahar (2018). Another method, not pursued here, is applied in Dinlersoz et al. (2019), and addresses selection bias using propensity score matching with logistic regressions.

essentially ‘‘scales-up’’ the number of observations in each cell so that they match those on official sources. Appendix B.1.7 gives further details on this post-stratification procedure.

Importantly, while re-sampling can correct for the fact that some cells may be better covered than others within ORBIS, the validity of this procedure —and the justification for random replication of firms within cells—is based on the assumption that, within each specific cell, ORBIS firms are representative of the true population (Gal, 2013).[88] Hence, it cannot correct for selection bias that would arise if companies with a specific set of characteristics (such as age, profitability, or TFP) have a higher propensity of consistently reporting all needed data items, and our results below should be interpreted in light of this shortcoming.[89]

Overall, correcting for the uneven distribution of country-year observations or using employment- and turnover-based re-sampling weights to replicate the size and sectoral structure of the actual population of firms in each country-year, leave our previous conclusions largely unchanged. Table 10 shows that (positive gross) capital flows in emerging countries consistently lead to relatively higher credit changes of low TFP firms, with even stronger estimates. The differential effects of negative capital inflows are however not statistically significant, but recall from Table 8 that these are especially pronounced for shorter lags. Indeed, if we repeat the weighted regressions for CF evaluated contemporaneously, Table C.14 in the Appendix confirms a significant divergence in credit allocation across low and high TFP firms when foreign funding dries up. As for advanced countries, Table 10 recognizes the strong asymmetries observed earlier, whereby inflows of liquidity generally do not affect differentially the credit flows of firms that differ in their productivity, while low productive firms in periods of negative capital inflows tend to face milder reduction in credit.

All told, the results for advanced and emerging economies highlight notable contrasts; the impact of capital inflows (when they are both positive and negative) on cross-firm credit allocation appears particularly strong in emerging countries, while more advanced banking sectors seem on average to better cope with a rise in loanable funds, although episodes of foreign disinvestment still induce larger corrections in lending among higher productive firms.

[88] Thus, for instance, firms with less than 10 employees in retail trade in Hungary are allowed to be poorly covered, but the average firm should be close to the one in the true population for that cell.

[89] On a side note, as regards how accurate our country-industry-size-year TFP median indicators are, we took some conservative steps to ensure the underlying number of available units is large enough to draw sensible productivity distribution. In our baseline setup, we group firms within broad sectors and two size classes only, and ensure that a minimum of 30 firms appear in each stratum. For instance, as reported in column (1) of Table 1, the median number of firms within a stratum is 968 and 154 for the 10th percentile. Some of these steps are relaxed in the robustness section.

Table 10. Contrasts betwen CEE12 and Adv10 Samples, WLS results

Margin Changes	**Intensive + Extensive** excluding years a firm stays unlevered							
Country coverage:	**Emerging Countries (CEE12)**				**Advanced Countries (Adv10)**			
Weighting Schemes:	No	ctry×year	empl	turnover	No	ctry×year	empl	turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{OUT\ -\ IN}}$	0.089	0.126	1.182	0.228	-0.243***	-0.280***	-0.340***	-0.331***
	(0.37)	(0.46)	(1.56)	(0.45)	(-4.47)	(-2.69)	(-3.69)	(-4.21)
◇ $D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{IN}}$	-0.504***	-0.609***	-0.913***	-0.699***	-0.011	0.026	-0.009	-0.011
	(-5.05)	(-6.01)	(-3.22)	(-4.04)	(-0.36)	(0.42)	(-0.20)	(-0.29)
◇ $D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{OUT}}$	-0.415*	-0.484*	0.269	-0.471	-0.254***	-0.254***	-0.348***	-0.342***
	(-1.80)	(-1.82)	(0.35)	(-0.95)	(-5.15)	(-2.72)	(-3.97)	(-4.69)
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{OUT\ -\ IN}}$	-0.005	0.014	0.032	0.000	-0.025***	-0.049***	-0.053***	-0.043***
	(-0.17)	(0.41)	(0.46)	(0.00)	(-3.47)	(-3.92)	(-4.69)	(-4.41)
◇ $D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{IN}}$	-0.076***	-0.090***	-0.092***	-0.077***	-0.004	-0.002	0.002	0.000
	(-6.32)	(-6.79)	(-3.65)	(-4.90)	(-1.13)	(-0.29)	(0.40)	(-0.04)
◇ $D^{TFP}_{i,t-1}$ × $\mathrm{CF_{c,MAt,t\text{-}2}}^{\mathbf{OUT}}$	-0.081***	-0.077**	-0.060	-0.077*	-0.028***	-0.051***	-0.051***	-0.043***
	(-3.01)	(-2.44)	(-0.88)	(-1.69)	(-4.27)	(-4.55)	(-5.04)	(-4.87)
Firm $\mathrm{Controls_{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i, s×t, c×t, c×s	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1022273	1022273	1022273	1022273	6306073	6306073	6306073	6306073
◇ Intensive changes	852717	852717	852717	852717	5433808	5433808	5433808	5433808
◇ Extensive changes	169556	169556	169556	169556	872265	872265	872265	872265
◇ Stay Unlevered	0	0	0	0	0	0	0	0
Number of firms	222376	222376	222376	222376	1173633	1173633	1173633	1173633

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}{\times}D^{OUT}\big){+}\gamma D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}{+}\delta_1 D^{TFP}_{i,t-1}{\times}D^{OUT}{+}\delta_2 D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where Ψ is defined in each panel of the table. $y_{i,t}$ denotes the outstanding financial debt of firm i in year t. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. Except for columns 1 and 5 that are estimated using OLS, the rest of the columns are estimated using WLS, where the re-sampling weights are defined as follows: weigth ‘‘*ctry×year*’’ is equal to the inverse of the number of a country's observations in a given year as a share of all observations in that year (i.e. $w_{c,t}{=}N_t/N_{c,t}$); weigths ‘‘*empl*’’ and ‘‘*turnover*’’ are based on the number of employees or turnover, respectively, in each SDBS country-industry(2digits)-size(4 size classes based on the number of employees) class cell to ‘‘scale up’’ the number of ORBIS observations in each cell so that they match those observed in the OECD's SDBS aggregate data. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. D^{OUT} denotes an outflow dummy which equals 1 when capital inflows are negative. We multiplied these negative inflows by -1, so that higher CF^{OUT} implies an increase in capital outflows, i.e., non-residents disinvest to a greater extent. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1

6.4 Zoom on SMEs and Macro Industries

SMEs are not a homogeneous group as micro, small and medium-sized firms are different in various ways. Our previous results may also mask important heterogeneity across industries.[90] Table C.15, reported in the Appendix for brevity, presents results for these two dimensions.

The estimated effect on our interaction term is negative and highly statistically significant for both small and medium firms, which make up the bulk of observations, while coefficients for micro firms are statistically insignificant and switch signs across dependent variables. Across macro industries, the heterogeneity is not obvious. Results suggest that capital inflows raise relatively more the debt of low TFP firms not only within the manufacturing sector, in line with Gopinath et al. (2017)'s findings, but also within services, especially in the distributive trade services sectors (i.e., wholesale and retail trade) as well as in the construction sector once we take account of both intensive and extensive margin credit changes; the differential effect is less clear for firms in other services.[91]

Further on cross-industry heterogeneity, we rely on Rajan and Zingales (1998)'s sectoral measure of external finance dependence (EFD), defined in Appendix B.2.1, and augment our main interaction term with a dummy splitting sectors at the median EFD. To the extent that capital inflows affect the supply of external financing, we expect its effect to be stronger among firms in industries that are historically more dependent, for technological reasons, on external funds to finance their investment. Reinforcing our interpretation of supply effects induced by capital inflows, Table C.15 show that the negative differential between high and low TFP firms is especially pronounced for industries with above median EFD; the estimated difference between high- and low-EFD sectors is large, although not very precisely estimated.

6.5 Robustness Checks

We analyze the robustness of our main findings along several dimensions. In particular, we explore i) alternative ways of measuring firm's debt, ii) various capital inflows measures, including their supply side component, iii) different settings with respect to the construction of the TFP dummy, and iv) several proxies of firm-level productivity. The results of the paper hold across these robustness checks.

[90] Appendix Tables B.3 and B.5 give the sample breakdown by sectors, and size classes, respectively.

[91] The negative and significant effect within the manufacturing sector is reassuring given that output and TFP estimates are considered to be more reliable than in other sectors.

Definition of firms' debt

In the baseline analysis, we rely on financial debt that includes all short- and long-term interest-bearing debt, i.e., loans and credit lines payable to credit institutions and corporate bonds. As our sample mainly covers SMEs, we consider it to be a good proxy for firms' aggregate bank debt positions—as argued in Section 3.1. This variable, however, is not perfectly identified in ORBIS and sometimes wrongly included among other liabilities items, resulting in a large number of firms reporting zero debt. Alternatively, in Appendix Table C.16, we use a broader measure as the sum of current and non-current liabilities, which has better coverage,[92] but comprises trade credit and other liabilities not payable to financial institutions. Our interaction of interest remains strongly negative and statistically significant, regardless of whether we use this broad-based definition for the same baseline sample of firms (column 2), or for a sample nearly two and a half times larger (column 3), or if it is decomposed as the growth in short- and long-term liabilities (columns 4 and 5, respectively).

Capital inflows variables

Secondly, we explore different capital inflows measures, and report the estimates for various timing lags in Table 11 for the intensive margin and in Appendix Table C.17 for both lending margins—coefficients are scaled by one capital flow standard deviation. Results are similar when we refine our baseline measure using only the "other investment" liabilities component (column 1)—removing portfolio debt—that is more closely related to bank inflows.

Next, in columns (3–6), we consider debt inflows measures that are constructed from the BIS cross-border bank positions, which have the benefit of being collected from the main lending (reporting) countries instead of the borrower (counterparty) country.[93] The first one (column 3) is based on the Locational Banking Statistics (LBSR) data, and use for each counterparty country c the available BIS's break- and exchange rate-adjusted change (in terms of GDP) in cross-border claims (XBC) in the form of loans—abstracting from other debt holdings made by banks—of internationally active banks located in all reporting countries vis-à-vis all borrowing sectors. The second measure (column 4) focuses instead on cross-border banking inflows to banks and the non-bank private sector only, and is estimated following Avdjiev et al. (2018). These two yield a very similar picture as our baseline.

[92] With total liabilities, we are able to re-introduce the observations pertaining to Ukraine (2012–14) and Romania (2003–9) that were initially excluded due to the misreporting issues on financial debt.

[93] Appendix B.2.2 provides further details on the construction of these BIS-based measures.

Table 11. Robustness, Alternative Capital Inflows Variables

Margin Changes: **Intensive only** *Dependent variable*: $\Delta\ln(y_{i,t})$

Data Source:	BOP-based		BIS-based				BOP	BIS
Capital Inflows Type: *Note: reported coefficients multiplied by one standard deviation of CF*	CF Total Debt **Baseline**	Other Invest.	ΔXBC all sectors (LBSR)	ΔXBC private (LBSR)	ΔFC private (CBS)	$\Delta LCLC$ private (CBS)	**Supply-driven** $\hat{\lambda}_c\ CF^{\text{World}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,t}}$	-0.707***	-0.844***	-0.504**	-0.595***	-0.886***	-0.293	-1.220***	-0.589***
	(-3.00)	(-3.60)	(-2.39)	(-2.76)	(-4.36)	(-1.34)	(-5.47)	(-3.05)
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,MAt,t-1}}$	-1.138***	-1.243***	-0.743***	-0.827***	-0.832***	-0.539**	-1.278***	-0.556***
	(-4.59)	(-5.01)	(-3.29)	(-3.53)	(-3.82)	(-2.40)	(-5.33)	(-2.71)
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,MAt,t-2}}$	-1.390***	-1.456***	-1.044***	-1.131***	-1.066***	-0.683***	-1.652***	-0.911***
	(-5.42)	(-5.65)	(-4.47)	(-4.79)	(-4.87)	(-3.08)	(-6.38)	(-4.03)
$\text{Firm Controls}_{\text{i,t-1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i,$s\times t$,$c\times t$,$c\times s$	yes	yes	yes	yes	yes	yes	yes	yes
Observations	826217	826217	826217	826217	826217	818100	826217	826217
Number of firms	183521	183521	183521	183521	183521	182801	183521	183521

Note: This table reports the results of estimating $\Delta\ln(y_{i,t})=\alpha+\beta\big(CF_{c,MA,t,t-q}\times D^{TFP}_{i,t-1}\big)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of financial debt of firm i in year t. D^{TFP} is a dummy that equals 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. *CF* is our country-specific capital inflows variable normalized by its GDP and measured as the moving average from year t-q to t (q=0,1,2). It is defined as follows: in columns 1-2, *CF* is based on BOP data and captures the private total debt inflows, or only the other investment component; in columns 3-4, *CF* is based on BIS's LBSR data and captures cross-border loans to all sectors, or to the private sector only; in columns 5-6, *CF* is based on BIS's CBS data and captures total foreign claims (in all instruments, to the private sector) or local claims in local currency, respectively; columns 7-8 use the fitted values of world total debt inflows (BOP-based, cf. column 1) or world cross-border banking inflows (BIS-based, cf. column 3). Appendix B.2.2 provides full definitions on BIS-based measures. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

The third BIS-based measure (column 5) relies on a broader definition of bank inflows. Organized around the residency principle, the BOP and LBSR data capture direct cross-border lending to non-bank private borrowers or non-affiliated banks (inter-bank flows) and intra-bank flows to subsidiaries or branches in the recipient country. However, the credit resident foreign-owned banks extend locally to other banks or firms is not, in itself, recorded as an inflow since the overseas parent bank is not directly involved. This indirect route represent a growing share of foreign banks' involvement (Milesi-Ferretti and Tille, 2011), and since the global financial crisis, we observe a substitution of international banks' cross-border flows by local lending by affiliates (IMF, 2015).[94] Local banking of foreign affiliates is nonetheless captured by the BIS's Consolidated Banking Statistics (CBS). We

[94]In our 12 CEE countries, foreign banks hold a large share of local banking system assets, on average 72% over 2003–2017, reaching as high as 96% for Estonia, 89% for Croatia, while shares for Ukraine and Slovenia are respectively 39% and 28% (sources: national statistical agencies, ECB).

thus draw on the latter to build an aggregate and estimated measure of bank inflows as the break- and currency-adjusted changes in *total foreign claims* (FC) in all instruments from all reporting countries to the recipient private sectors (see e.g., Houston et al., 2012; Karolyi et al., 2018). While this variable offers a more complete view on the overall domestic reliance on foreign banks and their role as engine of credit growth, strictly speaking, it overestimates this reliance since part of foreign affiliates' funding sources comes from local deposits. Again, we find a negative differential effect towards low TFP firms and similarly in column (6) when CF is measured solely as the change in local claims by affiliates in local currency ($LCLC$).[95]

Finally, we analyze the extent to which changes in push determinants of foreign debt inflows account for the documented negative differential effect towards low productive firms. Capital inflows could reflect changes in both foreign funding supply and domestic funding demand—e.g. see Chart 6 on emerging Europe in Amiti et al. (2017). To isolate its supply side component, we first project, for each country c in our sample, the country-specific debt inflows $CF_{c,t}$ (and in column 8, the change in cross-border claims on the private sector from column 5) on a constant and on their world counterpart over the entire sample period (as in, Cesa-Bianchi et al., 2018; Cingano and Hassan, 2020).[96] If supply factors from country c do not affect world capital flows—the typical small open-economy assumption—the fitted values $\hat{\lambda}_c \, CF_t^{\text{World}}$ can be interpreted as the supply side component of debt inflows into the country c private sector, which are unlikely to be caused by events within the country.[97] Results in columns 7 and 8 show that global flows raise relatively more the credit growth of ex-ante low TFP firms, and confirm that our core finding are mostly driven by the changes in push factors of foreign capital flows. It is less clear, however, if demand and supply-driven capital inflows hold opposing or additive effects on credit allocation across firms.

[95] Cross-border claims and local claims by foreign affiliates might bear different informational costs of screening and monitoring of borrowers, but our results are consistently negative regardless of whether we focus on FC, XBC or LCLC. This result should be set against the findings of IMF (2015), wherein the shift from cross-border banking to more activities by foreign affiliates is associated with a potential positive impact on financial stability (see also Karolyi et al., 2018).

[96] For each country c, CF^{World} aggregates debt inflows across all (minus c) countries from our cleaned BOP data (or LBS data), divided by the sum of corresponding nominal GDPs. This approach follows Blanchard et al. (2015), and is also closely related to Blanchard et al. (2017), in which these global flows are interacted with country-specific dummies.

[97] An alternative strategy, developed by Amiti and Weinstein (2018)—and applied to the BIS banking datasets by Amiti et al. (2019) and Avdjiev et al. (2021)—relies on the existence of bilateral claims to decompose banking inflows into common shocks, and idiosyncratic supply and demand shocks, using counterparty country-time and reporting country-time fixed effects. See also Aldasoro et al. (2020) for the construction of instruments for aggregate international bank lending. Unfortunately, we cannot apply these as much of the public data on bilateral lending pairs are marked as confidential.

Setting for the productivity dummy

Thirdly, as summarized in Table C.18 in the Appendix, our results withstand several alternative settings regarding the construction of our firm productivity dummy D^{TFP}. Specifically, columns (2-3) show that our results are similar when the productivity dummy is based on ex-post characteristics (assuming banks' rational expectations), or is time-invariant (averaging TFP across all years). As shown in columns (4-6), our results are also robust to alternative aggregate levels to which the median productivity cutoff is computed from. While high granularity is desirable, the level should be large enough to ensure the median is computed from a sufficient number of firms in each group. Compared to the baseline case, estimates in column (4) are based on the final analysis samples (in which firms with missing financial debt are excluded), while column (5) compares firms within the same industry using the 53 Nace 2-digit sectors, instead of the 26 Klems sectors, and finally column (6) compares firms within the same size category using four refined categories (micro, small, medium and large) rather than only two. In column (7), we look at debt allocation by firms' productivity using a continuous measure of firm-level TFP rather than an indicator variable if the firm is above or below its industry's median. Results are qualitatively similar to the baseline, albeit this specification focuses essentially on within-firm dynamics.[98]

Productivity variables

Lastly, we consider alternative firm-level productivity measures, whose results for different cutoffs are reported in Table 12 for the intensive margin and in Appendix Table C.19 for both margins. Our results are unchanged if we allow the output elasticities to vary by narrowly defined industries (column 2), where the production function estimation is performed separately for every 4-digit industry pooling all countries together, rather than for each country and 2-digit industry. We obtain smaller negative differential effects in column (3) when we group our firms based on labor productivity (defined as real value added over cost of employees or, in unreported regressions, as real value added per worker).

[98] A negative coefficient on $\hat{\beta}$ indicates that capital inflows increase credit growth in years when a firm's TFP is lower than its lifetime average. Unlike our baseline specification, this estimation does not, strictly speaking, shed light on the heterogeneous impact of capital inflows across firms with different productivity within the same industry. But, if one assumes that this within-firm estimated pattern holds for a broader comparison between firms, then the estimated differential effect, reported in square brackets, suggests that a 1 percentage point cumulative increase in debt inflows raises the annual debt growth rates of firms at the 25th percentile of the *overall* distribution of TFP by 0.223 percentage point more than of firms at the 75th percentile.

Table 12. Robustness, Alternative Productivity Variables

Margin Changes: **Intensive only**	*Dependent variable*: $\Delta\ln(y_{i,t})$				
Productivity Variable	$TFPR$ **Baseline**	$TFPR$ (4-dig. sectors pooled)	LP	$TFPR^C$ (markup adjusted)	MRP^K (markup adjusted)
	(1)	(2)	(3)	(4)	(5)
Panel A: TFP cutoff, p50					
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.276***	-0.246***	-0.130***	-0.239***	-0.254***
	(-5.42)	(-4.98)	(-2.80)	(-4.14)	(-4.56)
Observations	826217	828654	816533	716796	745337
Number of firms	183521	183593	182490	160357	162995
Panel B: TFP cutoff, p33–p66					
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.381***	-0.438***	-0.188***	-0.283***	-0.353***
	(-5.67)	(-6.20)	(-2.85)	(-3.87)	(-4.59)
Observations	564662	567167	559419	490018	501480
Number of firms	138656	138090	138849	120446	122289
Panel C: TFP cutoff, p25–p75					
$D^{TFP}_{i,t-1}$ × $\mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.454***	-0.518***	-0.242***	-0.422***	-0.356***
	(-5.25)	(-5.76)	(-2.98)	(-4.43)	(-3.68)
Observations	401762	405032	396328	351550	360796
Number of firms	104075	103794	104471	90865	92750
Firm $\mathrm{Controls}_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Delta\ln(y_{i,t}){=}\alpha{+}\beta\big(CF_{c,MA,t,t-q}{\times}D^{TFP}_{i,t-1}\big){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where y is firms' financial debt. D^{TFP} is a time-varying dummy that equals 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median (p50) productivity in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-size-year level. The productivity measure is defined as the log-TFP in column 1 where the production function estimation is performed separately for each country and 2-digit industry, while in column 2 the estimation is done for every 4-digit industries. In column 3, we use the labor productivity (real VA over cost of employees). Column 4 uses the revenue log-TFP adjusted from firm-specific markups, and column 5 uses the marginal revenue product of capital, see Appendices A.2 and A.3 for further details. *CF* is the private debt inflows of country c normalized by its GDP and measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and our productivity measure. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Then, in the fourth column, firm productivity is measured as revenue TFP purged from firm-specific and time-varying markups, that are retrieved following the methodology proposed by De Loecker and Warzynski (2012)—as described in Appendix A.2. Due to a lack of information on firms' output quantities and prices, we must rely on firm revenues, deflated by 2-digit industry deflators at best, to proxy for physical output when estimating the production function. We end up with a firm-level revenue TFP, which can be decomposed into physical productivity and output prices (Foster et al., 2008), i.e., $TFPR_{it}{=}TFPQ_{it}{+}p_{it}$ (all in logs). It is thus evident that differences of estimated revenue productivity across firms within industries might confound true technical efficiency with unobserved differences in firm-level prices which in turn reflect other factors like input prices, product differentiation, market structure and market power. Hence, a natural concern is that our results that capital inflows induce an increase of the relative supply of credit towards firms with low TFPR can be interpreted as an allocation away from higher price and higher markup firms, thus higher profitable firms, but not necessarily away from firms with higher technical efficiency. An allocation towards a firm with less market power but potentially higher efficiency relative to a ‘‘stagnant monopolist’’ may be welfare-enhancing.[99] Reassuringly, column (4) shows that our core results are qualitatively unaltered after this markup adjustment.

Finally, we classify firms based on their initial marginal revenue product of capital, corrected from firm markup—as computed in Appendix A.3. Importantly, results in column (5) reveals that following capital inflows, firms with initially high MRP^K, despite facing larger credit frictions, as other frictions that prevent them from investing as much as desired, experience a smaller credit growth relative to their low marginal product industry peers.

7. Conclusions

The question how cross-border financial flows are intermediated by the local banking sector and whether these funds are channeled to their more productive use bears important implications on a recipient country's productivity and long-run growth. But the available evidence is still scarce, and results are not always univocal. This paper attempts shedding new light by exploring whether, in which direction, and through which channels foreign debt inflows influence the domestic allocation of credit within industries across firms that differ in their ex-ante productivity. Leveraging on a large panel of private small firms and on specifications with a rich set of fixed effects, we contribute to the literature by analyzing the bank lending channel and the type of firms that benefited the most from these inflows within the context of emerging economies, in a sample of 12 bank-dominated CEE countries from 2003 to 2017.

Are these flows going where they should go? The answer appears to be negative. We find that private debt inflows lead to a disproportionate increase in credit growth of low TFP firms relative to their more productive industry peers. This negative differential effect materializes through the intensive margin of credit and the extensive margin (on entry), and for both the

[99] The fact that our focus is on SMEs, who can be viewed as price takers, already eases the concern of falsely identifying a firm with higher margins and earning larger profits as being more productive.

manufacturing and services sectors. The differentials are especially pronounced within SMEs, for industries with high external financial dependence, and when the comparison focuses on the tails of the TFP distribution. Our results occur mostly when foreign capital is driven by global supply factors as opposed to changes in pull determinants within the recipient country.

We show also that the impact on the allocation of credit is not limited to capital inflows surges, but extends to periods of negative capital inflows, wherein low TFP firms face in general a milder reduction in credit, which could be symptomatic of zombie lending. Interestingly, estimates from a sample of 10 more advanced countries show that foreign capital is also associated with a higher flow of credit to low TFP firms, yet the differentials are significantly smaller, and more asymmetric, limited to periods of foreign disinvestment.

Although firms with the lowest TFP are inefficiently large relative to units with higher capital returns and extending relatively more credit to these firms appears in itself inefficient (Hsieh and Klenow, 2009), this additional credit in periods of inflows may enable them to finance productivity-enhancing investments and eventually to catch up; but this does not seem to be the case, if anything, when exposed to an increase in credit, firms with high initial TFP levels show by far the largest relative TFP acceleration, while a contraction in credit causes a reduction of firm TFP growth for both type of firms. These results lend further support to the view that capital inflows tend to induce a misallocation of credit away from more productive and inefficiently under-resourced firms that could use additional funds in a more productive way, or the least could attract more inputs to upscale.

Why would banks allocate relatively more credit to low TFP firms when capital flows in? We conjectured that productivity would stand for other firm dimensions entering the banks' optimal risk-return profile, in particular firms' collateral and risk characteristics. Along these lines, we show that debt inflows do not necessarily relax banks' demand for collateral, but tend to favor debt accumulation by firms with high preexisting collateral that were financially unconstrained, which rules out the possibility that inflows would have helped alleviate the burden of credit constraints borne disproportionally by low TFP firms. While this result is broadly in line with the size-dependent borrowing constraints observed in Gopinath et al. (2017), where capital inflows are directed to high net-worth but unproductive firms, we believe it provides only a partial explanation for our core results. In accordance to an observed risk hypothesis, where the use of collateral is positively correlated with borrowers' riskiness, our results suggest that risk considerations from banks pursing higher returns contribute ultimately to our baseline findings. In other words, bank-intermediated capital inflows got directed more towards low TFP firms because these firms are on average relatively riskier, and endowed with more collateral. These results are consistent with nascent empirical works on the risk-taking channel of capital inflows.

A growing body of literature has emphasized the bank-lending channel in driving capital misallocation across firms in the wake of capital inflows, but little attention has been paid on the financial sector risk-taking incentives brought about by capital inflows and how credit, if allocated based on risk characteristics, feeds through to the misallocation of production factors. Quantifying the impact of this risk-taking channel of capital inflows on aggregate productivity is a fruitful avenue for future research. More generally, our results point to the need to carefully monitor who this credit is flowing to, especially in small open economies where capital inflows' intermediation is pervasive. Further, there is not necessarily a trade off between financial stability (bank risk-taking aspect) and allocative efficiency, to the extent that the correlation between risk and productivity is negative. In this respect, it would seem useful to study how macro-prudential policies, such as reserve requirements, shape changes in credit allocation associated with capital inflows.[100]

Our paper has some limitations, which should be addressed in future research. The main shortcoming stems from the inability to match information of the ending banks with information for the borrowing firms which would provide an edge in the identification of credit supply and help identify the banks more exposed to debt inflows. Moreover, while we find some interesting contrasts between our sample of CEE countries and a sample of more advanced banking sectors, it may be of interest, in light of results in Dinger and te Kaat (2020) or Cantú et al. (2022) for instance, to exploit within-country variability in bank characteristics, and examine the heterogeneous impact of capital inflows on the allocation of credit by banks with differing funding structure or balance sheet strength—e.g., liquid vs. illiquid, better vs. worse capitalized, with high vs. low level of NPLs. Hence, a natural extension of our paper would be to combine our firm sample with bank data using information on bank-firm relationships from Kompass (Giannetti and Ongena, 2012). Ideally, it would be interesting to analyze this question by employing granular loan-level cross-country data from the recent analytical credit register of the European System of Central Banks.

[100] To the extent that prudential policy is effective in limiting bank risk-taking—which is not a given, e.g. Jiménez et al. (2017); Camors et al. (2019)—the negative credit and real effects of a tightening might be mitigated by an improved credit allocation towards less risky but more productive firms.

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Appendices

A. Firm-level Productivity Estimation

This Appendix lays out the details on the firm-level productivity estimation that builds on the approach developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), Wooldridge (2009) and Petrin and Levinsohn (2012). We then introduce firm-level measures of revenue TFP adjusted from firm-specific markups and of marginal revenue products of capital, that are used in the robustness section.

A.1 Production Function Estimation – Revenue TFP (TFPR)

For each firm i in period t, we assume a Cobb Douglas production function in value added (VA_{it}) with two inputs of labor (L_{it}) and capital (K_{it}):

$$VA_{it}{=}Z_{it}L_{it}^{\beta_l}K_{it}^{\beta_k} \tag{A.1}$$

The object of interest is Z_{it}, which is unobserved by the econometrician. We take the natural log of the above equation, and decompose lnZ_{it} into two terms ($lnZ_{it}{=}\beta_0{+}\epsilon_{it}$), where β_0 measures mean efficiency across all firms over time t, and ϵ_{it} can be regarded as deviations from the mean capturing (i) unobserved factors affecting firm output such as managerial ability, (ii) measurement error in output and inputs, and (iii) random noise (Eberhardt and Helmers, 2019). Using small case notations for logs, the production function in its logarithmic form is given by: $va_{it}{=}\beta_0{+}\beta_l l_{it}{+}\beta_k k_{it}{+}\epsilon_{it}$, where l_{it} is the static input labor that can vary freely at each t, and k_{it} is the dynamic capital input, which is partly determined by its previous stock and enter the firm's state space.

The firm-specific error term ϵ_{it} can be decomposed into a term capturing an anticipated productivity Hicks neutral shock ω_{it}^*—which is observed by the firm and hence affects its input choices—and an additional term capturing unexpected productivity shocks or other sources of errors such as measurement errors v_{it}—which is unobserved and does not affect input choices (Eberhardt and Helmers, 2019). Though ω_{it}^* can be correlated with l_{it} or k_{it}, v_{it} is restricted to be orthogonal to l_{it}, k_{it} and ω_{it}^*. The production function becomes:

$$va_{it}{=}\beta_0{+}\beta_l l_{it}{+}\beta_k k_{it}{+}\omega_{it}^*{+}v_{it} \tag{A.2}$$

We are interested in estimating firm-level total factor productivity ω_{it}^*. Estimating the production function in Eq. (A.2) with OLS will result in biased estimates of β_l and β_k because a firm's choice of input quantities depends on its TFP (ω_{it}^*)—more productive firms will use more inputs. One approach to deal with such simultaneity bias is to use a function of observables that carry information on ω^*_{it}, referred to as a control function. We use the control function proposed in Levinsohn and Petrin (2003), with the GMM-framework advocated by Wooldridge (2009) as implemented by Petrin and Levinsohn (2012).

In the control function approach proposed by Olley and Pakes (1996), the endogeneity bias is handled by proxying ω^*_{it} with an inverted investment demand function. Olley-Pakes identified conditions under which firm-level investment (conditional on capital stock) is a strictly increasing function of a scalar, i.e. the firm-level unobserved productivity shock. This strict monotonicity implies that one can invert this investment demand function, and thus control for the unobserved productivity shock by conditioning on a nonparametric representation of that inverse function.

Levinsohn and Petrin (2003) use a similar approach, but invert instead an intermediate input demand function. They propose to use material inputs as a proxy since they argue that investment tends to be lumpy and does not react smoothly to productivity shocks (the investment demand function is not strictly increasing). A firm's intermediate input decision is a function of the firm's state variables ω^*_{it} and k_{it}:

$$m_{it}{=}f_t(\omega^*_{it}{,}k_{it}) \tag{A.3}$$

With some assumptions on the firm's production technology, Levinsohn and Petrin (2003) show that the demand function f_t is monotonically increasing in ω^*_{it}. Together with the fact the productivity term ω^*_{it} is the only scalar unobservable entering the inversion function[101], this allows inversion of the intermediate demand function, so that the unobservable ω^*_{it} can be expressed solely as a function of two observables k_{it} and m_{it}:

$$\omega^*_{it}{=}f_t^{-1}(m_{it}{,}k_{it}) \tag{A.4}$$

A final identification restriction in Olley-Pakes and Levinsohn-Petrin is that productivity is governed by a first-order Markov process:

$$\omega^*_{it}{=}E(\omega^*_{it}|\omega^*_{it-1}){+}\xi_{it} \tag{A.5}$$

where the productivity innovation ξ_{it} is uncorrelated with current values of the fixed input

[101] Griliches and Mairesse (1998) noted that this places strong implicit restrictions on additional firm-specific econometric unobservables in the model, ruling out for instance unobserved heterogeneity across firms in adjustment costs of capital, in demand or labour market conditions.

k_{it}, but not necessarily with the variable input l_{it}, which is chosen at the same time the productivity shock is realized—this is part of the source of the simultaneity problem. It satisfies $E(\xi_{it}|\omega^*_{it-1})=0$.

If we knew f_t^{-1}, we could control for the unobservable ω^*_{it}:

$$va_{it} = \beta_l l_{it}+\phi_t(m_{it},k_{it})+v_{it}, \tag{A.6}$$

$$\phi_t = \beta_0+\beta_k k_{it}+f_t^{-1}(m_{it},k_{it}). \tag{A.7}$$

However, f_t^{-1} is unknown. Still, we can estimate ω^*_{it} by approximating the non-parametric function ϕ_t with a third order polynomial approximation in m_{it} and k_{it}, as follows:

$$\phi_t \approx \delta_0+\sum_{a=0}^{3}\sum_{b=0}^{3-a}\delta_{ab}k_{it}^a m_{it}^b \tag{A.8}$$

The Levinsohn-Petrin estimation procedure follows Olley-Pakes and consists of:

- Recovering $\hat{\beta}_l$ and $\hat{\phi}_t$ by estimating via OLS the following equation:

$$va_{it}=\delta_0+\beta_l l_{it}+\sum_{a=0}^{3}\sum_{b=0}^{3-a}\delta_{ab}k_{it}^a m_{it}^b+v_{it} \tag{A.9}$$

  where β_0 is not separately identified from the intercept of ϕ_t.

- Recovering $\hat{\beta}_k$, which begins by computing the estimated value for ϕ_t using :

$$\hat{\phi}_t=\hat{va}_{it}-\hat{\beta}_l l_{it}, \qquad \hat{\phi}_t=\hat{\delta}_0+\sum_{a=0}^{3}\sum_{b=0}^{3-a}\hat{\delta}_{ab}k_{it}^a m_{it}^b \tag{A.10}$$

- From the assumption on the markov process and for a given β_l, we have

$$E(va_{it}-\beta_l l_{it}|k_{it},\omega^*_{it-1})=\beta_k k_{it}+E(\omega^*_{it}|k_{it},\omega^*_{it-1})+E(v_{it}+\xi_{it}|k_{it},\omega^*_{it-1}) \tag{A.11}$$

  Note that $E(v_{it}+\xi_{it}|k_{it},\omega^*_{it-1})=0$ by construction, since k_{it} is pre-determined and v_{it} is orthogonal to (l_{it},k_{it},m_{it}). We thus obtain:

$$va_{it}-\beta_l l_{it}=\beta_k k_{it}+E(\omega^*_{it}|\omega^*_{it-1})+v_{it}+\xi_{it} \tag{A.12}$$

- Letting $E(\omega^*_{it}|\omega^*_{it-1})=h(\omega^*_{it-1})$ and noting that $\omega^*_{it-1}=\phi_{t-1}-\beta_k k_{it-1}$, β_k can be consistently estimated from the following second stage regression :

$$va_{it}-\hat{\beta}_l l_{it}=\beta_k k_{it}+h(\hat{\phi}_{t-1}-\beta_k k_{it-1})+v_{it}+\xi_{it} \tag{A.13}$$

  with $\hat{\beta}_l$ and $\hat{\phi}_t$ obtained from the first stage regression, and the unknown function h again approximated by a fixed order polynomial.

As argued by Ackerberg et al. (2015) however, the coefficient on labor input may not be identifiable in the first stage regression Eq. (A.9). This problem arises if labor input is optimally chosen by firms upon observing their productivity, so that $l_{it}{=}\varphi(k_{it},\omega^*_{it})$ and $l_{it}{=}\varphi(k_{it},f_t^{-1}(m_{it},k_{it}))$. In that case, labor input becomes a function of the same variables as the control function, which precludes identification of its coefficient at the first stage.

Wooldridge (2009) proposes a GMM procedure that estimates all the coefficients in the production function in one stage by directly approximating the function $h(.)$ with a polynomial in (k,l,m). This estimator is simpler than the non-linear estimator by Ackerberg-Caves-Frazer and it does not rely on the estimates of ϕ from the first stage, thus avoiding bootstrapping to compute the standard errors.

Specifically, the first equation of the system is identical to the first-stage equation of Olley-Pakes and Levinsohn-Petrin (Eq. A.9). Under the assumption that the errors v_{it} are not observed by the firm, all the right-hand-side variables are exogenous. The most straightforward choice of instrumental variables for Eq. (A.9) is simply $z_{it1}{=}(l_{it},c_{it})$, where c_{it} is a vector containing all the terms of the polynomial in (m_{it},k_{it}). These instruments correspond to the OLS first-stage regression in Olley-Pakes and Levinsohn-Petrin.

The interesting insight of Wooldridge (2009) is that the assumption that productivity follows a first-order Markov process results in a second equation:

$$E(\omega^*_{it}|k_t,l_{t-1},k_{t-1},m_{t-1},\ldots){=}E(\omega^*_{it}|\omega^*_{it-1}){=}h(\omega^*_{it-1}){=}h(f_{t-1}^{-1}(k_{t-1},m_{t-1}))$$
$$\omega^*_{it}{=}h(\sum_{a=0}^{3}\sum_{b=0}^{3-a}\delta_{ab}k^a_{it-1}m^b_{it-1}){+}\xi_{it}$$
$$va_{it}{=}\beta_0{+}\beta_l l_{it}{+}\beta_k k_{it}{+}h(\sum_{a=0}^{3}\sum_{b=0}^{3-a}\delta_{ab}k^a_{it-1}m^b_{it-1}){+}\xi_{it}{+}v_{it} \tag{A.14}$$

where all the coefficients of interests can be identified with appropriate instruments. The set of instruments for Eq. (A.14) would include fixed variables such as capital in period t, lagged variable inputs in period $t{-}1$, and functions of these inputs: $z_{it2}{=}(k_{it},l_{it-1},c_{it-1},q_{it-1})$, where q_{it-1} refers to nonlinear functions of c_{it-1} and l_{it-1}. While all the instruments used for the second Eq. (A.14) are also valid for the first Eq. (A.9), the contemporaneous m_{it} and l_{it} are only valid instruments for Eq. (A.9) as they are likely to be correlated with the innovation in the productivity ξ_{it}. Thus, the orthogonality conditions differ across these two equations:

- In the first Eq. (A.9), the orthogonality condition on the error v_{it} is given by:

$$E(v_{it}|l_{it},k_{it},m_{it},l_{it-1},k_{it-1},m_{it-1},\ldots,l_{i1},k_{i1},m_{i1}){=}0 \tag{A.15}$$

that is the error term v_{it} is uncorrelated with labor, capital, and material input, but also with all lags of these.

- In the second Eq. (A.14), the orthogonality condition on the error is given by:

$$E(\xi_{it}+v_{it}|k_{it},l_{it-1},k_{it-1},m_{it-1},...,l_{i1},k_{i1},m_{i1})=0 \tag{A.16}$$

that is the error term $v_{it}+\xi_{it}$ has to be independent of the current and lagged values of capital and the lagged values of labor and material inputs.

Although Wooldridge (2009) proposes to jointly estimate Eqs. (A.9) and (A.14), we only use a single equation instrumental variables method applied to Eq. (A.14) following Petrin and Levinsohn (2012). This decision is made because if l_{it} and m_{it} are determined simultaneously as in the Ackerberg-Caves-Frazer setting, β_l cannot be identified by the first equation. The second equation would still generally identify β_l and β_k provided we have the orthogonality conditions in Eq. (A.16). Effectively, k_{it}, k_{it-1} and m_{it-1} act as their own instruments and l_{it-1} acts as an instrument for l_{it}. Thus, in our study, we estimate Eq. (A.14) with Pooled IV, using k_{it}, l_{it-1} (excluded instrument), m_{it-1} and k_{it-1}, as well as polynomials containing m_{it-1} and k_{it-1} of order up to 3 as instruments for l_{it}. That is,

$$\begin{aligned} va_{it}=&\beta_0+\beta_k k_{it}+\beta_2 k_{i(t-1)}+\beta_3 m_{i(t-1)}+\beta_4 k^2_{i(t-1)}+\beta_5 m^2_{i(t-1)}+\beta_6 k^3_{i(t-1)}+\beta_7 m^3_{i(t-1)}\\ &+\beta_8 k_{i(t-1)} m_{i(t-1)}+\beta_9 k_{i(t-1)} m^2_{i(t-1)}+\beta_{10} k^2_{i(t-1)} m_{i(t-1)}\\ &+\beta_l l_{i(t-1)}+n_{it} \end{aligned} \tag{A.17}$$

The empirical implementation of this pooled IV specification is discussed in Appendix B.1.5.

With estimates of $\hat{\beta}_k$ and $\hat{\beta}_l$ in hand, firm-level log TFP is retrieved as the difference between log value added and the fitted values for log capital and log labor as follows:

$$\begin{aligned} \text{with} \quad & TFP_{it}=lnZ_{it}=\beta_0+\epsilon_{it}=\beta_0+\omega^*_{it}+v_{it}\\ \text{and because} \quad & va_{it}-\beta_l l_{it}-\beta_k k_{it}=\beta_0+\epsilon_{it}\\ \text{we obtain} \quad & T\hat{F}P_{it}=va_{it}-(\hat{\beta}_k k_{it}+\hat{\beta}_l l_{it}) \end{aligned} \tag{A.18}$$

A.2 TFPR Measure Adjusted For Firm Markups

Our firm-level revenue-based TFP (TFPR) can be decomposed into physical productivity and output prices (Foster et al., 2008), i.e., $TFPR_{it}=TFPQ_{it}+p_{it}$ (all in logs). In order to mitigate the limitations from not observing firm-level prices, we introduce in the robustness section a revenue TFP measure corrected from estimated firm- and time-varying mark-ups.

Using the fact that price-cost markup is the ratio of firm-specific price over marginal costs ($\mu_{it}=\frac{P_{it}}{MC_{it}}$), subtracting the estimated log revenue productivity with the estimated log-markup yields an adjusted productivity measure that excludes firm-level prices (Garcia-Marin and Voigtländer, 2019): $TFPR_{it}-\ln(\mu_{it})=(TFPQ_{it}+p_{it})-(p_{it}-\ln(MC_{it}))=TFPQ_{it}+\ln(MC_{it})$.

The methodology for deriving markups follows the production approach proposed by Hall (1986) and revisited by De Loecker and Warzynski (2012), in which firm-level markups are recovered from revenues data without relying on market-level demand information. The essential insight is that for any variable input free of adjustment costs the markup drives a wedge between the input's output elasticity and its revenue share. Under cost minimization and flexibility of at least one the inputs, the markup can be computed by dividing the output elasticity with respect to the flexible input by that input's expenditure share, as follows:

$$\mu_{it}\equiv\frac{P_{it}}{MC_{it}}=\left[\frac{\partial Y_{it}}{\partial V_{it}}\frac{V_{it}}{Y_{it}}\right]\bigg/\left[\frac{P^V_{it}V_{it}}{P_{it}Y_{it}}\right]=\frac{\text{Output Elasticity}}{\text{Expenditure Share}} \tag{A.19}$$

where P (P^V) denotes the price of output Y (of the variable input V). We consider employment L as the flexible input V and derive the markup as the ratio of the output elasticity of employment and the share of labor costs in revenue, that is $\hat{\mu}_{it}=\frac{\hat{\beta}^j_L}{ws_{it}}$.[102]

Ultimately, the markup-adjusted log revenue productivity ($TFPR^C_{it}$) is retrieved as the difference between the raw revenue-based productivity and the log of the estimated markup, i.e. $TFPR^C_{it}=TFPR_{it}-\ln(\hat{\mu}_{it}) \equiv TFPQ_{it}+\ln(MC_{it})$.

[102] $\hat{\beta}^j_L$ are retrieved from estimating the production function using Wooldridge (2009)'s GMM estimation method, and as such, are the same elasticity estimates as the ones used to compute our revenue productivity measure (TFPR). Regarding the denominator, De Loecker and Warzynski (2012) propose to use a variant of the wage share, $ws_{it}=WL_{it}/\widetilde{VA}_{it}$, where labor costs WL are directly observed from the data and the corrected value added $\widetilde{VA}$ is estimated. This adjustment helps to retrieve only the part of output, i.e. value added, that is anticipated by the firm since firms do not observe unanticipated shocks to production and are thus assumed to minimize costs based on a prediction of value added. The prediction is based on fitting a rich polynomial function (of order 2) of deflated inputs on deflated value added: $va_{it}=h(k_{it},l_{it},mit)+\alpha_t+\epsilon_{it}$, which is estimated separately for each country and two-digits industry controlling for year fixed effects. Using the residuals obtained from the above regressions ($\hat{\epsilon}_{it}$), the predicted level of VA is computed as $\widetilde{VA}_{it}=VA_{it}/\exp(\hat{\epsilon}_{it})$.

A.3 MRPK Measure

We also introduce in the robustness section a firm-level measure of marginal revenue product of capital, adjusted from firm-specific markups.[103]

Consider a firm i, belonging to sector j, that produces output Q using a Cobb-Douglas production function with capital K and labor L inputs, $Q_{it}{=}A_{it}K_{it}^{\beta_j^K}L_{it}^{\beta_j^L}$. In a model in which firms compete monopolistically and faces an inverse demand curve $P(Q)$ featuring variable elasticity of substitution, i.e. implying a markup that varies over time and across firm, the marginal revenue product of capital K can be derived as follows:

$$MRP_{it}^{K}{\equiv}\frac{\partial P_{it}(Q_{it})Q_{it}}{\partial K_{it}}{=}P_{it}\frac{\partial Q_{it}}{\partial K_{it}}{+}\frac{\partial P_{it}}{\partial Q_{it}}\frac{\partial Q_{it}}{\partial K_{it}}Q_{it}{=}\underbrace{P_{it}\frac{\partial Q_{it}}{\partial K_{it}}}_{VMP_{it}^{K}}\underbrace{\left[1{+}\frac{Q_{it}}{P_{it}}\frac{\partial P_{it}}{\partial Q_{it}}\right]}_{\mu_{it}^{-1}}{=}\underbrace{\frac{P_{it}}{\mu_{it}}}_{MR_{it}}\underbrace{\frac{\partial Q_{it}}{\partial K_{it}}}_{MP_{it}^{K}}{=}\frac{\beta_j^K}{\mu_{it}}\frac{P_{it}Q_{it}}{K_{it}} \tag{A.20}$$

where μ_{it} is the price-cost markup[104], MP_{it}^{K} is the marginal product of capital, MR_{it} denotes marginal revenue and VMP_{it}^{K} refers to the money value of the marginal product of capital when the market is competitive.[105] Using Eq. (A.20), we obtain estimates of firm-level marginal revenue product of capital by multiplying the capital elasticity from production function estimation by the inverse of the value added share of capital and the estimated firm-level markup. We then take the log of this measure.

[103] We are unable to get estimates of MRP^L since our markup estimation relies on the labor input L as the flexible input.

[104] Suppose a firm, with price setting power, produces output Q for a total cost $C(Q)$ and faces an inverse demand function $P(Q)$. Its profit is given by $\pi{=}P(Q)Q{-}C(Q)$. The first-order condition for the profit maximization problem implies $\frac{\partial P_{it}}{\partial Q_{it}}Q{+}P{-}\frac{\partial C}{\partial Q}{=}0$. $MC{\equiv}\frac{\partial C}{\partial Q}{=}\frac{\partial P}{\partial Q}Q{+}P{=}P(\frac{\partial P}{\partial Q}\frac{Q}{P}{+}1){\equiv}MR$. Hence, in Eq. (A.20), we use the fact that $\mu_{it}^{-1}{=}\frac{MC_{it}}{P_{it}}{=}\frac{\partial P_{it}}{\partial Q_{it}}\frac{Q_{it}}{P_{it}}{+}1$.

[105] Note that in competitive market, $MR_{it}{=}P_{it}$ and $MRP_{it}^{K}{=}VMP_{it}^{K}$.

B. Data Appendix

B.1 ORBIS Cleaning Procedure and Data Construction

This Appendix describes the ORBIS data cleaning procedures that we followed in constructing our final samples of analysis, guided by the recommendations laid out in Kalemli-Özcan et al. (2015), Gopinath et al. (2017), and Gal (2013), among others.

B.1.1 Cleaning Each Vintage Raw Data

Before merging vintages together, the raw data in each vintage are cleaned as follows:

- We use the BvD correspondence table to account for firms which had their unique company identifiers BvD ID changed over time. The 2005 vintage requires a special treatment for firms in former Yugoslavia (country code YU) or in former Serbia-Montenegro (country code CS). Using the numerical part of firm IDs, we assign the country code for Serbia (RS) if a firm belongs to Serbia in later vintages, and the country code for Montenegro (ME) for firms assigned to Montenegro in later vintages. Where it is not possible (i.e. firms not appearing in later vintages), we exclude the remaining firms with country codes YU and CS.
- We drop firm-year observations with missing currency or missing account closing date.
- We construct the calendar year variable using the account closing date variable, as follows: if the month of the closing date is later than June 1st then the current year is assigned, otherwise the previous year is assigned.
- For company-headquarter of a group that report both consolidated accounts C2 (integrating the statements of all its affiliates, subsidiaries, etc.) and an unconsolidated account U2 (the statement not integrating the statements of the controlled entities), we drop C2 accounts to avoid double-counting. We thus retain unconsolidated accounts U1 and U2 as well as consolidated accounts C1, although the vast majority of firms in the final sample have unconsolidated accounts.[106]

[106] *Consolidated account C1*: account of a company- headquarter of a group, aggregating all companies belonging to the group (affiliates, subsidiaries, etc.), where the company headquarter has no unconsolidated account. *Consolidated account C2*: account of a company-headquarter of a group, aggregating all companies belonging to the group (affiliates, subsidiaries, etc.) where the company headquarter also presents an unconsolidated account. By definition, the number of accounts with the C2 code equals the number of accounts with the U2 code. *Unconsolidated account U1*: account of a company with no consolidated account.

- We clean the data off basic reporting mistakes by removing firm-year observations if:
  - at least one of the following variables are recorded negative: fixed assets and its three sub-categories, current assets and its three sub-categories, total assets, non-current liabilities and its 2 sub-categories, current liabilities and its 3 sub-categories, total liabilities, sales, cost of employees and depreciation and amortization. This filter is not applied on operating revenues, shareholder funds, nor on cash and cash equivalents (due to overdraft accounts);
  - firms report sales, operating revenue, total assets, and the sum of shareholders funds and liabilities as 0;
  - employment is either 0, negative, or greater than 2 millions;
  - the accounting period is less than 12 months;
  - the derived country code based on the BvD ID numbers does not correspond to BvD's country ISO code.
- We treat the set of duplicates with same ID-CONSCODE-YEAR , but different month of publication. We drop the duplicates that have an abnormal month of publication compared with the usual month used in the history of the firm. Remaining duplicates are filtered on, as follows: retain the duplicate with closing date closest to the end of year; if operating revenue is available, select the one with the largest operating revenue; the remaining duplicates have the same operating revenue and closing date, so we retain the one with better coverage in the main variables used in the later analysis.
- For the 2005 ORBIS vintage, we go through the process of converting the 4-digit NACE Rev. 1.1 industry classification to the more recent 4-digit NACE Rev. 2 classification. The official correspondence table between the two systems does not always yield a one-to-one mapping. We supplement it by using information for firms in the 2010 vintage wherein both industry codes are available. Otherwise we manually match codes by reading the codes' descriptions. This correspondence table is available upon request.
- We convert the firms' reporting currency of accounts to the official local currency of the country. We will use later on the GDP deflator in the official local currency with base year 2010, which relies on an irrevocable euro conversion rate for the recent Eurozone

Unconsolidated account U2: account of a company with a consolidated account. *Limited number of financial items LF*: account of a company with only a limited number of information included.

members. For countries that change their currencies before 2010 (such as Slovenia and Slovakia), the currency of financials for all firm-years is the official local currency as of today. If the change of currency occurs after 2010, for instance for Estonia in 2011, then we express all the financials of Estonia in EEK before 2011 and from 2011, all financial data is recalculated to EUR.

- We impute missing values based on 11 accounting properties. We distinguish derived variables, like total fixed assets, from fundamental variables, i.e., tangible assets, intangible assets and other fixed assets. If all but one variable in an accounting property is missing, then we replace it with the residual according to its accounting identity. In cases where only one of the fundamental variables belonging to an accounting property is missing, such as intangible assets, and the sum of the other fundamental variables (i.e., other fixed assets plus tangible assets) is close (with a 0.01 margin error) to the derived variable (i.e., total fixed assets), then we replace the missing fundamental (i.e. intangible assets) by 0. If the derived variable is close to one of the fundamental variables, then the other fundamental variables, which are missing, are set to 0. On average, a given vintage would have around 20% of total firm-year observations with at least one variable imputed, but only 0.8% imputed by a non-zero value.
- Finally, we do a broad consistency check of balance sheet information. For each of the 11 accounting properties, if not respected (with a margin of error of 0.1), we replace all variables that enter an identity by missing.

B.1.2 Merging Vintages

After implementing these basic cleaning steps and data harmonization for each vintage, we merge the financial data from individual vintages together. Starting from the earlier/oldest vintage, we merge it with the further out vintage with update and replace options, that is for firms-years appearing in both vintages, we retain the non-missing values for the variables coming from the most recent vintage. A non-missing value in the earlier vintage will not be replaced with a missing in the recent vintage.

A complication arises when a fundamental variable is non-missing in the old vintage but missing in the new vintage. If this variable is updated in the new vintage by the old vintage value, it might not necessarily respect the accounting properties of the new vintage. Two methods can be pursued to insure more consistent merging between vintages. One conservative possibility is to replace the non-missing value in the old vintage by a missing value, so that when merging both vintages, the resulting observation is missing. The other possibility, adopted here, is to change the missing new vintage value into the old vintage non-missing value if and only if it respect the new vintage accounting properties. If these updated values were not consistent, then we use the conservative option so that the resulting observation remains missing. Although this step will impact the final samples' coverage, all our results remain consistent if the conservative option is adopted.

B.1.3 General Cleaning Steps

- To ensure consistency and comparability of monetary variables across countries and over time, we convert all nominal financial variables in local official currency into real 2010 U.S. dollars using country-year specific GDP deflators (with 2010 base and in local currency) obtained from the World Bank and the 2010 annual exchange rate (simple mean of average monthly rates) between the official currency and the U.S. dollar (where 1Off=x$). Of note, some specific variables that enter into the estimation of firm-level TFP such as value added, cost of employees, material costs and capital stock are also deflated using country-sector-year deflators.
- For firms with different years of incorporation, we choose the older one. Regarding sector classification, we assume a constant NACE Rev. 2 4-digit code per firm. Note that NACE codes are constant for all years in a specific ORBIS vintage. We first treat invalid NACE industry codes using information on NAICS or SIC codes when available or if a previous data vintage record a valid NACE code. We replace by missing the remaining invalid ones. For firms reporting several NACE codes, we select the one with the highest frequency, or ultimately the most recent one. We update missing information on other string variables which are unlikely to change over time with values from other years. If information is missing in all years, they remain missing. Note that since we do not rely on a firm's age for our analysis, i.e. number of years since year of incorporation, we retain firms with missing year of incorporation. Conversely, we exclude firms with missing information regarding their industry of activity.
- Concerning sectoral coverage, and following Lenzu and Manaresi (2019), we drop firms operating in: Agriculture (Nace 1-3, letter A), Mining and Quarrying (Nace 5-9, letter B), Utilities (Nace 35-39, letter D-E), Postal Services and Courier Activities (Nace

53), Scientific activities and R&D (Nace 72), Education (Nace 85), Health services (Nace 86-88, letter Q), Sport, Arts, Entertainment Act (Nace 90-3, letter R), Public administration and defense, compulsory social security (Nace 84, letter O), Activities of households as employers (Nace 97-8, letter T), Activities of extraterritorial organizations and bodies (Nace 99, letter U), in order to avoid analyzing sectors with high government ownership, and/or due to the inherent difficulties in measuring output for these sectors; Financial and insurance activities (Nace 64-66, letter K) and Real estate activities (Nace 68, letter L) since firms operating in these industries are themselves credit providers and heavily regulated sectors; and finally firms operating in Tobacco (Nace 12) and Pharma (Nace 21) which tend to be large multinational firms.

- We further drop firm-year observations with negative values for current liabilities, non-current liabilities, loans, and long term debt, and those for which long term debt or loans exceeds total liabilities.
- We compute total liabilities as either the difference between the sum of shareholder funds and liabilities and shareholder funds, or as the sum of current liabilities and non-current liabilities. We drop firm-year observations if any of these two definitions of total liabilities yield negative values. We compute the ratio of the two variables of total liabilities and drop the firm-year observations if the ratio is not equal to 1 (with a margin of error of 0.1 in the ratio).
- We retain firm-year observations with positive shareholder funds (book's equity). Negative shareholders' equity implies that a company's liabilities exceed its assets, and is usually connected with accounting methods used to deal with past losses' accumulation (losses viewed as liabilities carried forward until future cancellation, thus a flag of financial distress.
- We drop firm-year observations that violate the accounting rules such that the sum of the book value of shareholder funds and liabilities and that of total assets should be equal to each other (with 0.1 margin error in the ratio), and that the book value of shareholder funds should be inferior or equal to that of total assets (with 0.1 margin error in the ratio).
- We drop firm-year observations with zero or negative values for the wage bill, and strictly negative values for operating revenues.

- We now impose stricter internal consistency conditions on firms' balance sheet information. We drop firm-year observations if any of the seven following ratios are below 0.98 and above 1.02: 1) the sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of total fixed assets; 2) the sum of stocks, debtors, and other current assets as a ratio of total current assets; 3) the sum of fixed assets and current assets as a ratio of total assets; 4) the sum of capital and other shareholder funds as a ratio of total shareholder funds; 5) the sum of long term debt and other non-current liabilities as a ratio of total non-current liabilities; 6) the sum of loans, creditors, and other current liabilities as a ratio of total current liabilities; 7) the sum of non-current liabilities, current liabilities, and shareholder funds as a ratio of the variable that reports the sum of shareholder funds and total liabilities. An alternative option would be to estimate their distribution for each country separately, and each 2-digit industry, and then exclude extreme values that are identified simultaneously as outliers (using the 0.1 and 99.9 percentiles) by both the country-level and the industry level trimming. This leaves however certain ratios with large values far from 1, thus we implement the first option.
- Regarding value added, which is computed in the baseline case as the difference between operating revenues and material costs, we drop firm-year observations with negative values. By definition, the wage bill cannot be larger than value added. We construct the ratio of nominal cost of employees to nominal value added and drop extreme values in the bottom 1 percentile and top 99 percentile of the distribution of the ratio, simultaneously identified as outliers at the country level and at the industry 2-digit level. We further drop firm-year observations with ratios higher than 1.1.
- Regarding the capital stock measure, which is computed in the baseline case as the book value of fixed assets, we drop firm-year observations for which the ratio of nominal capital stock over nominal total assets is strictly superior to 1.
- We restrict our attention to firms that have at least a median balance sheet total of 50,000 US dollars (GDP-deflated to 2010 dollars) across all years of activity.

B.1.4 VA and GFCF Deflators

Some nominal variables that enter into the estimation of firm productivity are converted into real ones by applying more specific deflators, rather than country-year 2010 base GDP deflators. We collect country-sector-year specific deflators in value added (VA) and in gross fixed capital formation (GFCF) (2010 base) obtained from different data sources. The main data source is Eurostat which provides series at the 2-digit industry level. We supplement it with data from OECD STAN, World Input-Output Tables (WIOD) and national sources. All deflators are rebased to 2010=100.

Because all countries do not have all the 2-digit level information in all the years, missing values at the 2-digit industry-level for a particular country-year have been filled up by applying the growth rate in the price index at a more aggregate level. Starting from the immediate higher level of aggregation, this algorithm is continued until reaching the 1-letter detail of the industry classification. For cases where the 1-letter level is missing, then we use the VA and GFCF implicit deflators from the WDI World Bank dataset broken down into 4 major sectors (Agriculture, Industry, Manufacturing, Services). If still missing, we replace it with its country-year level average.

Regarding VA deflators, 56.5% of country-sector-year observations are defined at the 2-digit industry-level, while the rest are approximated at higher level of aggregation, on average 2.57 sectors higher. Eurostat represents 79.7% of observations, national sources 13.8% (for Bosnia Herzegovina and Ukraine only), STAN 5%, WIOD 1.16%, and WDI 0.34% (for Ukraine only). On the other hand, for GFCF deflators, 25.8% of country-sector-year observations are approximated at country-year level. Only 28.1% of observations are defined at the 2-digit industry-level, while the remaining 16.1% are approximated at a higher level of aggregation up to WDI macro sectors, with on average at 8.75 sectors higher level. Eurostat represents 61.7% of observations, national sources 5.8% (only for Serbia), STAN 2.1%, WIOD 4.4%, and WDI 25.86% (mainly for Bosnia Herzegovina, Ukraine and Croatia).

B.1.5 Estimation of the Factors' Elasticities and TFP

We impose a number of additional restrictions on the sample used specifically for the estimation of the production function's factor elasticities.

- We drop observations with missing information on the variables needed for the elasticities' estimation, i.e. real material costs, real value added (operating revenues - material costs), and real cost of employees, all single single-deflated by country-industry-year VA deflators, as well as real capital stock (fixed assets) single-deflated by country-industry-year GFCF deflators. We retain firms with at least 2 consecutive years.

- We further clean the capital stock measure. We drop entire firms if in any year they have a nominal capital to wage bill ratio simultaneously in the bottom 0.1% of the country-level and the 2-digit industry-level distributions. We drop firm-year observations with ratios higher than the 99.9 percentile or lower than the 0.1 percentile.
- Finally, in order to limit the influence of erratic or implausible firm-behavior, we exclude information for firms that report an extreme annual log-change in real value added, labor costs, or capital stock. We drop the firm-year observations for the years t and $t-1$ (the two years used in the growth rate measure) if at least one of the variables has a growth rate in t that is in the top or bottom 1% of the growth distribution (again simultaneously identified as extreme at the country-level and at the industry-level).

We face the trade-off between allowing β_l and β_k to vary as much as possible across countries and disaggregated industries, and retaining enough observations for meaningful estimations. For the baseline case, we estimate with Pooled IV the specification (A.17), laid out in Appendix A.1, separately for each (i.e., assuming homogeneity of elasticities at) country-2-digit sectors, with time dummies, and standard errors clustered at the firm-level.[107]

We adopt the following procedure. Within each regression at country-2-digit sectors, at least 500 observations are required for the estimation. Both $\hat{\beta}_l$ and $\hat{\beta}_k$ need to be strictly superior to zero and statistically significant at the 10% significance level. If at least one of these three conditions is not satisfied, then we resort to regressions ran at a higher degree of aggregation, that is at the country-sector level using the EU-KLEMS industry classification (26 categories instead of 74 2-digit NACE industries). In the cases where one of the conditions is still violated, no estimated coefficients are reported, and values of estimation-based TFP measures are left empty for the problematic strata.

As sensitivity tests, we also estimate the production function separately for each 4-digit industries, pooling all countries together and controlling for country and year fixed effects. Again, if at least one of the three aforementioned conditions is not satisfied, then we resort to regressions ran at 2-digit industry level.

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[107]We use the following command in Stata: (using Sergio Correia (2018)'s *ivreghdfe* Stata software)

ivreghdfe va_{it} $\quad k_{it}\ k_{it-1}\ m_{it-1}\ k^2_{it-1}\ m^2_{it-1}\ k^3_{it-1}\ m^3_{it-1}$
$k_{it-1}{\times}m_{it-1}\ k^2_{it-1}{\times}m_{it-1}\ k_{it-1}{\times}m^2_{it-1}$
(l_{it}=l_{it-1}), gmm2s cluster(i) absorb($Year_t$)

With $\hat{\beta}_k$ and $\hat{\beta}_l$, firm-level log TFP is retrieved as the difference between log value added and the fitted values for log capital and log labor as follows:

$$\begin{aligned} \text{with} \quad & TFP_{it}=lnZ_{it}=\beta_0+\epsilon_{it}=\beta_0+\omega^*_{it}+v_{it} \\ \text{and because} \quad & va_{it}-\beta_l l_{it}-\beta_k k_{it}=\beta_0+\epsilon_{it} \\ \text{we obtain} \quad & T\hat{F}P_{it}=va_{it}-(\hat{\beta}_k k_{it}+\hat{\beta}_l l_{it}) \end{aligned} \tag{B.1}$$

where va_{it} refers to the log of real value added (operating revenues - material costs), l_{it} to the log of real cost of employees, both of which are single-deflated by country-industry-year VA deflators, and k_{it} refers to the log of real capital stock (fixed assets) single-deflated by country-industry-year GFCF deflators. Of note, although observations with missing material costs do not enter into the estimation of the factor elasticities, firm TFP can be computed if the variables in Eq. (A.18) are available.

Finally, we drop the firm-year observations for the years t and $t-1$ if the change in log TFP in t is in the top or bottom 1% of the country-industry distribution.

B.1.6 Final Samples Formation

Our study concentrates on a sample of firms from 12 emerging countries in Central and Eastern Europe (CEE) over 2003–2017. Earlier years generally lack good coverage of companies and are thus excluded from the analysis.

We distinguish for our analysis four samples, of which three are used directly in the regressions and differ with respect to the definition of a firm's debt annual change as the dependent variable, while the fourth sample imposes less restrictions on data availability and is used for the computation of the productivity cutoffs.

- *Final Sample A*: smallest sample restricted to changes in the amount of a firm's financial debt on the intensive margin, that is conditional on firms having non-missing and non-zero outstanding borrowing in both t and $t-1$. Thus, we drop firm-year observations where the log-difference of outstanding financial debt is missing. The sample includes 826,217 observations with 183,521 firms.

- *Final Sample B*: larger sample that focuses on adjustments at both the intensive and extensive margins, that is conditional on firms having non-missing outstanding borrowing in both t and $t-1$, but allowing firms' entry into the credit market (zero in $t-1$) and firm's exit (zero in t). We drop firm-year observations where the DHS mid-point growth rate or the first difference of debt scaled by lagged assets is missing. Of note, these two dependent variables are set to missing if financial debt is equal to zero in both t and $t-1$. The sample has 1,022,273 observations with 222,376 firms.

- *Final Sample C*: close to sample B but includes years a firm stays unlevered, that is we set the DHS mid-point growth rate or the first difference of debt scaled by lagged assets equal to zero whenever financial debt is equal to zero in both t and $t-1$. The sample consists of 1,616,184 observations with 328,372 firms.

- *Final Sample D*: the largest sample where no restrictions is applied on the dependent variable on a firm's flow of credit, nor on the availability of firm-controls. This sample is not used directly in the regressions, but for the computation of the median (terciles or quartiles) productivity cutoff pooling all firms at the country-industry-year and size class (SME, large) level. The sample has 3,313,269 observations with 747,097 firms.

The first three samples (A-C) rely on a firm's financial debt positions that include all short-term and long-term interest-bearing debts. This measure, however, is not perfectly identified in ORBIS. As highlighted in Figure B.I below, we observe in our data extreme cases where short-term or long-term financial debt is zero for all firms in some country-years: loans seem to be wrongly attributed to the residual item other current liabilities or to trade credit, or vice-versa, and long term debt sometimes seems to be attributed to the residual item other non-current liabilities. Due to these misreporting issues, we have to exclude observations pertaining to Ukraine in the years 2012–14 and to Romania in the years 2003–9. In the robustness section, we depart from financial debt and measure firm's debt as the sum of current and non-current liabilities, which enables us to include back those problematic country-year observations.

For the first three samples, we retain firm-year observations if log-TFP in $t-1$ and $t-2$ is non-missing and if any firm controls in $t-1$ in collateral (tangible fixed assets/total assets), firm size (log of total assets), profitability (EBIT/total assets), external financial need (1 - (ROA/(1-ROA))), and growth opportunities (intangible assets/total assets) are non-missing.

To limit the potential impact of outliers, we winsorize variables before performing our empirical analysis. We winsorize at the 5 and the 95 percentiles the dependent variables in log-difference and in first difference scaled by lagged assets—the DHS mid-point growth rate is already bounded by construction. Collateral (tangible fixed assets/total assets) and the cash ratio are winsorized at the 99th percentile. We winsorize at the 1 and the 99 percentiles all other variables, such as the productivity measures, the other firm controls, and the financial constraint and risk proxies.

Figure B.I. Misreporting of Financial Debt Positions, Romania and Ukraine

B.1.7 Construction of Sampling Weights

In Section 6.3.2, in order to improve representativeness of our final samples along the industry and firm size dimensions to that of the whole population of firms within a specific country-year, we align our regression samples of firms with the distribution of the true firm population as reflected in the Structural Demographic Business Statistics (SDBS) collected by the OECD and Eurostat, which is based on administrative data from national sources. We follow closely the post-stratification procedure proposed in Schwellnus and Arnold (2008) and Gal (2013), and provide further details below.

Specifically, after filling up some of the missing values in the SDBS dataset (not all dimensions are available) under reasonable assumptions, we collect information in each year on the number of employees and on turnover in constant dollars for each cell of country, industry (using two-digit NACE codes) and four different groups of firm sizes: less than 10 employees, between 10 and 49 employees, between 50 and 249 employees, and 250 employees or more. As a side note, for this specific setup, we align the definition of size class to the definition employed in SDBS, which relies solely on the number of employees, while outside of this setup, our baseline definition is expressed according to the turnover, total assets and/or the number of employees of the firms (see Section 3.1). For Bosnia-Herzegovina and Serbia, OECD's SDBS data were not available, so population figures were extracted from the Eurostat SBS for Bosnia-Herzegovina and from the national Statistical Office for Serbia.

The weights in each cell are computed as the ratio of total employment according to the ORBIS sample to the total employment in SBDS, in each year of the sample. Turnover-based weights are obtained similarly. Note that a corresponding resampling weight is constructed for each final sample in a specific regression. Due to lack of data on the SBDS database and because some countries are poorly covered (such as Slovenia where around 31% of its total observations are not matched to SDBS figures) or not covered at all (the case of Ukraine), about 11.5%-16% of total firm-year observations in our samples based on European emerging countries, depending on the exact specification, were given a weight of 1 (i.e., no weight)—and about 2.5% of observations in the advanced countries samples.

Then, we assign a weight (an integer) to each firm-year observation in our final samples, which is always greater or equal to one—so that we do not loose firms already present—by randomly drawing firms until the sample mean of the weights of all firms in each stratum (country-industry-size-year) corresponds closely to the observed SDBS/ORBIS employment (or turnover) ratio for that cell. In other words, as thoroughly explained in Gal (2013), if the ratio of SDBS employment to ORBIS employment for a specific country-industry-size-year cell is 1.1, then the 10% "extra" employment is obtained by drawing firms randomly from the pool of ORBIS firms, such that the "extra" firms will make up for the missing 10%. In a different case, if the ratio is 2.4, then all firms are taken at least twice and only the remaining extra 40% will be drawn randomly.

As a last step, since a large part of the observed variability of the sampling weights is due to a small number of extreme weights, that are based on cells with very few non-randomly selected firms (around 11 firms per cell on average) —for which the assumption of within-cell representativeness is unlikely to be satisfied—we right-winsorize the distribution of firm weights to the 99.5 percentile. This avoid the situation where a few extreme weights can offset the precision gains from an otherwise better representation of the population. We obtain similar results if we retain only the cells with at least 15 firms.

The average amount of winsorized re-sampling weights (averaged across all years) needed per country and firm size class is shown in Table B.1, and the average weights per country and broad sector is presented in Table B.2. Summary statistics on the constructed re-sampling weights for the sample of Advanced countries are presented in Tables B.3 and B.4. We concentrate on the weights constructed for the two samples (samples B and C) for which regression results were tabulated in Table 10 and Appendix Table C.13. Regarding the firm size dimension (in terms of number of employees), we notice that re-sampling weights are much higher for the smallest firm-size classes, especially for micro firms, while medium and large firms tend to need the least amount of scaling up. This issue of small firms representativeness is particularly severe in countries like Hungary, Poland and Romania. Concerning the sectoral dimension, manufacturing sectors (letter C) have, on average, roughly two times smaller employment-based weights than the services sectors.

Table B.1. Sampling Weights, Average by Country and Size Class, Across All Years, Sample of Emerging Countries

	Sample B Intensive + Extensive margins excluding years a firm stays unlevered					**Sample C** Intensive + Extensive margins including years a firm stays unlevered				
Size class:	**1-9**	**10-49**	**50-249**	**250+**	**Avg.**	**1-9**	**10-49**	**50-249**	**250+**	**Avg.**
Weight Type: Number of Employees										
BA	11.9	3.4	3.4	4.0	7.8	9.8	3.0	3.0	8.5	6.7
BG	18.6	3.6	2.5	2.5	8.7	9.4	2.3	1.8	1.9	5.4
CZ	34.1	4.5	2.3	2.2	13.0	15.7	2.7	1.6	1.4	7.6
EE	12.0	4.2	6.1	2.0	8.4	8.4	3.2	4.7	2.2	6.2
HR	8.7	2.6	2.3	2.1	6.1	6.1	2.1	2.0	2.0	4.6
HU	232.5	21.2	5.1	4.3	49.5	139.6	16.8	4.1	2.9	37.3
PL	433.2	51.8	12.3	15.0	58.2	323.8	41.2	10.4	9.2	49.0
RO	602.8	101.3	5.6	3.1	15.7	466.5	75.0	3.9	1.9	17.2
RS	7.4	2.3	2.2	2.5	4.9	6.0	2.0	2.0	2.5	4.2
SI	7.3	2.2	2.8	1.9	5.4	6.2	2.0	2.4	1.7	4.8
SK	23.7	4.4	3.5	4.3	13.1	11.9	2.7	2.1	2.9	7.4
Avg.	27.1	11.3	5.6	7.6	16.5	18.5	8.5	4.5	4.7	12.2
Weight Type: Turnover										
BA	9.3	3.7	4.7	5.4	6.7	7.3	3.1	4.0	9.4	5.5
BG	14.0	3.4	2.8	2.5	7.1	7.3	2.3	2.0	2.0	4.5
CZ	26.7	4.5	2.7	3.2	10.9	13.2	2.8	1.8	1.7	6.6
EE	9.0	3.5	8.4	23.3	6.9	6.1	2.6	6.4	16.8	4.9
HR	6.0	2.3	2.7	1.9	4.5	4.2	1.9	2.3	1.8	3.4
HU	67.5	8.8	4.1	4.8	16.8	37.8	5.6	2.8	2.3	11.2
PL	59.4	6.8	4.0	5.7	9.2	41.8	5.2	3.1	3.5	7.2
RO	117.5	27.4	3.9	3.2	6.2	79.4	18.3	2.5	1.7	5.0
RS	4.1	2.2	2.5	2.6	3.2	3.3	1.9	2.2	2.4	2.7
SI	4.6	1.8	3.5	4.7	3.8	3.8	1.6	2.8	3.5	3.2
SK	12.4	3.7	4.2	7.1	7.9	6.1	2.2	2.5	4.2	4.4
Avg.	11.7	3.9	3.4	4.4	7.0	7.8	2.9	2.5	2.7	5.0

Note: The table presents summary statistics on the average amount of winsorized re-sampling weights (averaged across all years) per country and firm size class (in terms of number of employees). The country codes are BA (Bosnia-Herzegovina), BG (Bulgaria), CZ (Czech Republic), EE (Estonia), HR (Croatia), HU (Hungary), PL (Poland), RO (Romania), RS (Serbia), SI (Slovenia), and SK (Slovakia). SDBS data are unavailable for UA (Ukraine), and weights are set to 1.

Table B.2. Sampling Weights, Average by Country and Broad Sector, Across All Years, Sample of Emerging Countries

	Sample B Intensive + Extensive margins excluding years a firm stays unlevered										Sample C Intensive + Extensive margins including years a firm stays unlevered									
Broad sector:	**C**	**F**	**G**	**H**	**I**	**J**	**M**	**N**	**S**	**Avg.**	**C**	**F**	**G**	**H**	**I**	**J**	**M**	**N**	**S**	**Avg.**
Weight Type: Number of Employees																				
BA	6.4	6.6	7.3	5.4	42.1	8.6	17.8	13.2	.	7.8	5.6	5.8	6.1	5.0	35.6	5.6	12.2	12.6	.	6.7
BG	6.1	7.2	9.2	7.0	18.3	11.8	13.6	9.4	19.0	8.7	3.9	4.8	5.9	4.5	11.8	4.8	5.6	4.9	8.7	5.4
CZ	6.9	9.9	14.3	15.5	57.1	17.2	21.0	17.8	31.5	13.0	4.6	6.0	8.3	10.0	33.9	6.9	8.5	8.9	15.5	7.6
EE	5.7	11.9	8.3	4.5	11.7	17.9	18.3	11.0	.	8.4	4.3	8.7	6.1	3.9	9.1	9.2	10.1	7.5	.	6.2
HR	4.2	6.5	5.0	6.1	14.9	6.3	8.3	6.6	7.0	6.1	3.5	5.2	3.8	5.1	11.7	4.1	5.3	5.2	4.8	4.6
HU	21.1	63.8	56.5	47.7	79.3	73.6	117.0	59.6	156.3	49.5	17.9	51.7	41.5	41.1	76.2	39.4	57.3	41.2	122.8	37.3
PL	42.3	82.1	54.5	56.1	131.3	83.5	102.0	77.4	4.5	58.2	37.7	64.9	45.2	45.7	114.2	57.0	77.8	62.4	14.4	49.0
RO	9.1	13.7	23.4	23.9	20.2	50.2	26.2	14.8	.	15.7	8.4	17.7	25.6	16.0	49.5	31.6	37.8	15.0	8.4	17.2
RS	3.8	4.3	4.9	4.1	8.3	7.1	9.6	7.1	4.0	4.9	3.4	3.6	4.2	3.7	7.0	5.2	6.7	5.6	3.3	4.2
SI	3.2	6.1	6.8	4.0	12.1	5.9	9.9	9.1	4.7	5.4	2.9	5.4	5.9	3.7	10.9	4.2	7.8	7.3	3.8	4.8
SK	6.7	9.7	13.5	12.5	56.3	22.1	23.3	22.3	24.3	13.1	4.2	5.7	7.8	7.2	33.6	8.1	10.6	9.5	4.8	7.4
Avg.	11.5	17.9	17.3	13.1	31.9	21.6	23.3	20.6	15.4	16.5	9.2	13.1	12.7	10.4	24.6	12.6	13.9	14.0	9.2	12.2
Weight Type: Turnover																				
BA	6.1	6.1	6.4	4.9	17.7	7.1	17.7	11.0	.	6.7	5.2	5.1	5.2	4.6	13.8	4.3	11.8	12.1	.	5.5
BG	4.6	9.9	6.9	5.0	11.8	11.1	13.9	6.6	15.3	7.1	3.0	7.2	4.5	3.4	6.7	4.3	5.3	3.7	6.0	4.5
CZ	6.3	11.0	9.7	10.7	40.4	15.9	22.9	13.1	22.1	10.9	4.4	7.0	5.8	6.9	25.7	6.3	10.1	6.8	10.2	6.6
EE	5.4	11.2	6.8	4.5	7.0	13.2	12.2	6.4	.	6.9	4.0	7.8	4.9	3.7	5.4	5.6	6.6	4.3	.	4.9
HR	3.3	5.2	3.6	4.2	8.5	4.8	6.2	5.1	4.6	4.5	2.7	4.2	2.8	3.5	6.9	3.1	3.7	4.1	2.9	3.4
HU	9.7	21.8	15.8	18.9	27.8	29.8	39.3	20.7	59.1	16.8	7.3	16.8	9.8	12.3	21.6	16.0	20.2	11.0	39.2	11.2
PL	6.8	12.3	8.2	8.2	12.1	16.9	22.7	11.8	17.3	9.2	5.6	9.4	6.6	6.2	9.4	9.3	14.4	8.6	12.2	7.2
RO	4.0	5.8	8.7	7.6	9.2	22.6	9.8	4.8	.	6.2	3.1	5.0	6.6	4.8	13.0	10.6	9.1	4.7	6.6	5.0
RS	2.7	2.9	3.2	3.1	4.7	4.4	5.2	3.5	2.1	3.2	2.4	2.5	2.7	2.7	3.9	3.2	3.7	2.6	1.6	2.7
SI	3.0	4.4	3.1	3.1	6.6	4.1	6.0	5.4	3.8	3.8	2.7	3.8	2.6	2.7	5.8	3.1	4.5	4.1	3.1	3.2
SK	6.1	8.6	6.8	6.5	15.9	11.5	11.3	11.8	22.5	7.9	3.8	4.9	4.0	3.5	11.2	4.1	5.0	4.8	7.9	4.4
Avg.	5.0	8.3	6.3	5.8	13.2	10.2	12.4	8.8	10.7	7.0	3.9	6.2	4.6	4.4	9.9	5.4	6.9	5.4	5.9	5.0

Note: The table presents summary statistics on the average amount of winsorized re-sampling weights (averaged across all years) per country and broad sector, where letter C corresponds to Manufacturing, F Construction, G Wholesale and retail trade, I Accomodation and food service activities, H Transportation and storage, J Information and communication, M Professional, scientific and technical activities, N Administrative and support service activities, S Arts, entertainment and recreation. The country codes are BA (Bosnia-Herzegovina), BG (Bulgaria), CZ (Czech Republic), EE (Estonia), HR (Croatia), HU (Hungary), PL (Poland), RO (Romania), RS (Serbia), SI (Slovenia), and SK (Slovakia). SDBS data are unavailable for UA (Ukraine), and weights are set to 1.

Table B.3. Sampling Weights, Average by Country and Size Class, Across All Years, Sample of Advanced Countries

	Sample B Intensive + Extensive margins excluding years a firm stays unlevered					**Sample C** Intensive + Extensive margins including years a firm stays unlevered				
Size class:	**1-9**	**10-49**	**50-249**	**250+**	**Avg.**	**1-9**	**10-49**	**50-249**	**250+**	**Avg.**
Weight Type: Number of Employees										
AT	366.4	75.2	7.8	2.7	21.8	419.3	76.5	7.2	2.7	23.9
BE	111.9	6.7	2.2	1.9	17.0	84.4	5.1	1.7	1.6	14.8
DE	289.5	65.0	14.5	4.8	52.7	289.7	58.9	11.2	4.0	48.6
ES	13.2	3.1	2.4	2.9	8.7	10.1	2.7	2.2	2.9	7.1
FI	14.7	5.5	5.3	6.1	10.8	11.6	4.3	3.6	2.2	8.3
FR	20.9	5.7	3.6	3.3	11.9	17.3	5.1	3.4	3.3	10.5
IT	16.6	3.5	2.0	1.6	9.8	13.0	3.0	1.9	1.5	8.3
NO	62.0	99.8	23.3	5.1	75.7	56.2	104.8	39.7	5.2	75.3
PT	17.4	7.6	3.8	2.7	12.8	17.3	8.2	3.5	2.5	13.3
SE	9.2	5.5	8.4	11.8	8.3	6.1	3.6	4.7	5.3	5.5
Avg.	18.1	7.8	4.2	3.3	12.4	15.3	8.9	4.4	3.2	11.7
Weight Type: Turnover										
AT	27.3	19.7	4.8	2.1	6.1	26.1	18.2	4.4	2.0	5.8
BE	28.7	4.8	2.3	2.1	6.5	22.3	3.6	1.8	1.8	5.5
DE	68.8	29.2	8.7	4.1	19.8	50.0	22.2	6.4	3.4	14.6
ES	10.2	2.8	2.6	3.4	7.0	8.0	2.4	2.3	3.2	5.7
FI	10.4	4.6	5.4	11.5	8.3	7.9	3.4	3.3	3.4	6.0
FR	10.5	3.1	2.6	2.2	6.2	8.9	2.8	2.4	2.1	5.5
IT	9.0	2.4	2.0	1.6	5.6	6.6	2.0	1.7	1.5	4.5
NO	10.0	3.7	4.2	6.4	6.4	4.8	1.8	1.8	2.3	3.3
PT	7.2	2.4	2.2	2.4	5.1	5.8	2.1	1.9	2.1	4.3
SE	9.0	5.0	8.3	14.7	8.0	5.8	3.2	4.3	6.0	5.2
Avg.	9.9	3.4	3.1	2.6	6.6	7.5	2.8	2.6	2.3	5.2

Note: The table presents summary statistics on the average amount of winsorized re-sampling weights (averaged across all years) per country and firm size class (in terms of number of employees). The country codes are AT (Austria), BE (Belgium), DE (Germany), ES (Spain), FI (Finland), FR (France), IT (Italy), NO (Norway), PT (Portugal) and SE (Sweden).

Table B.4. Sampling Weights, Average by Country and Broad Sector, Across All Years, Sample of Advanced Countries

Sample B — Intensive + Extensive margins (excluding years a firm stays unlevered)

Broad sector:	C	F	G	H	I	J	M	N	S	Avg.
Weight Type: Number of Employees										
AT	7.7	21.5	31.8	.	.	23.6	35.1	23.4	.	21.8
BE	7.7	18.3	17.9	15.8	29.5	21.2	51.7	35.4	1.8	17.0
DE	29.9	67.1	60.0	58.5	140.3	59.0	66.3	99.4	100.1	52.7
ES	4.2	9.6	8.1	9.1	15.8	8.6	15.7	13.4	18.8	8.7
FI	6.5	9.4	9.9	10.4	15.2	22.4	20.5	18.0	15.0	10.8
FR	8.0	10.1	10.1	14.5	13.6	21.5	39.3	20.4	22.5	11.9
IT	5.6	9.2	11.6	11.2	20.1	8.7	16.5	14.1	14.1	9.8
NO	41.2	70.9	92.6	86.8	72.3	71.2	75.2	42.7	13.6	75.7
PT	9.0	12.4	14.0	25.9	11.0	13.2	26.6	20.9	7.6	12.8
SE	4.4	6.2	6.9	10.7	9.7	26.6	26.1	12.8	9.5	8.3
Avg.	7.1	12.2	12.7	14.5	15.9	14.8	25.5	18.8	18.8	12.4
Weight Type: Turnover										
AT	4.1	8.5	6.1	.	.	7.9	13.9	7.6	.	6.1
BE	4.0	7.7	6.1	7.6	13.6	8.5	16.2	11.8	3.2	6.5
DE	14.6	29.3	18.5	20.1	48.4	24.2	19.4	32.8	39.0	19.8
ES	3.7	9.6	6.1	6.3	12.1	6.1	12.5	8.1	14.0	7.0
FI	6.2	6.7	7.4	8.5	11.2	17.3	14.2	12.5	9.6	8.3
FR	4.6	5.8	5.2	6.4	7.1	9.2	18.8	9.1	9.9	6.2
IT	3.0	6.8	6.1	4.9	13.3	4.9	11.4	6.0	7.6	5.6
NO	3.9	5.6	4.9	11.2	8.9	13.9	13.6	10.6	6.9	6.4
PT	2.9	5.2	3.9	12.5	9.0	8.9	24.0	12.3	6.1	5.1
SE	4.3	6.6	6.4	11.7	7.9	27.0	23.0	12.9	10.1	8.0
Avg.	4.0	7.2	5.8	7.1	9.8	7.9	15.1	9.0	10.1	6.6

Sample C — Intensive + Extensive margins (including years a firm stays unlevered)

Broad sector:	C	F	G	H	I	J	M	N	S	Avg.
Weight Type: Number of Employees										
AT	7.7	27.9	34.0	.	.	25.7	32.7	25.2	.	23.9
BE	6.4	19.1	14.6	12.6	31.7	18.6	40.6	29.6	1.0	14.8
DE	26.6	65.6	53.2	54.5	136.0	51.6	65.2	89.2	94.5	48.6
ES	3.6	7.8	6.5	8.1	12.5	6.7	11.7	10.8	14.2	7.1
FI	5.4	7.1	7.6	8.7	11.3	13.9	14.3	12.5	12.0	8.3
FR	7.2	8.9	8.8	13.3	12.0	17.0	32.7	17.9	18.6	10.5
IT	5.1	7.9	9.8	9.1	15.7	6.4	12.1	10.3	11.0	8.3
NO	34.8	64.3	101.9	72.6	76.4	49.9	59.7	40.8	21.1	75.3
PT	9.7	13.6	14.5	25.8	11.3	11.3	23.0	17.8	6.0	13.3
SE	3.2	4.0	4.4	9.4	5.9	11.7	13.1	7.9	5.3	5.5
Avg.	6.5	11.3	12.8	13.0	14.1	12.2	20.6	15.5	14.9	11.7
Weight Type: Turnover										
AT	3.9	7.8	5.8	.	.	7.4	12.7	8.0	.	5.8
BE	3.2	6.7	5.1	6.4	11.8	8.1	11.3	9.6	1.4	5.5
DE	11.0	24.6	12.4	16.5	33.3	15.4	13.6	23.6	27.5	14.6
ES	3.2	8.3	4.8	5.4	9.8	4.4	9.1	6.4	10.5	5.7
FI	4.9	5.0	5.4	6.8	7.5	9.0	9.2	7.3	7.6	6.0
FR	4.1	5.1	4.7	5.9	6.4	7.5	15.7	8.0	8.4	5.5
IT	2.5	5.5	4.7	3.8	9.6	3.3	9.1	4.3	5.4	4.5
NO	2.3	3.4	2.5	7.7	4.0	3.3	4.5	4.8	3.9	3.3
PT	2.6	4.7	3.2	11.0	7.2	7.1	18.9	9.8	4.9	4.3
SE	3.1	4.3	4.1	9.9	4.9	10.9	11.1	7.8	5.9	5.2
Avg.	3.3	5.9	4.6	5.9	7.8	5.3	10.6	6.8	7.7	5.2

Note: The table presents summary statistics on the average amount of winsorized re-sampling weights (averaged across all years) per country and broad sector, where letter C corresponds to Manufacturing, F Construction, G Wholesale and retail trade, I Accomodation and food service activities, H Transportation and storage, J Information and communication, M Professional, scientific and technical activities, N Administrative and support service activities, S Arts, entertainment and recreation. The country codes are AT (Austria), BE (Belgium), DE (Germany), ES (Spain), FI (Finland), FR (France), IT (Italy), NO (Norway), PT (Portugal) and SE (Sweden).

B.2 Other Data Construction

B.2.1 Industry's External Finance Dependence

Following Rajan and Zingales (1998), we use U.S. firm-level data between 1980-1996 from Compustat to build a time-invariant industry-specific external financial dependence (EFD) measure based on the share of capital expenditures not financed with cash flow from operations.

First, to smooth any temporal fluctuations, we sum both capital expenditures and cash flows from operations over the 1980–1996 period for each firm. We add the restriction that the firm-level EFD ratios are set to missing if based on less than 3 years. Then, using the sums obtained in the first step, we compute firm-level EFD measures by taking the ratio of capital expenditures minus cash flows from operations over capital expenditures (i.e., $\frac{capx - CashFlow}{capx}$).[108]

Compustat records a firm's industry using US NAICS 2002 6-digit codes, which has broad direct correspondence with the 4-digit Nace Rev.2 classification. Whenever official tables contains a multiple matching, we manually match codes by reading their long descriptions so that each NAICS 2002 code is assigned to a unique Nace Rev.2 2-digit code. The manual correspondence table is available upon request. The industry-level EFD is computed as the median ratio across firms for each 2-digit Nace sector s, thereby obtaining a measure that is representative for the industry and not too heavily influenced by outliers. We require a minimum of 10 firms for each sector to avoid situations where only few observations determine the characteristics of an industry. Finally, we assign each sector to the high or low EFD group depending on whether its dependence on external financing is above or below the median sectoral value.

[108] Cash flows from operations (CashFlow) is defined as the sum of funds from operations (*fopt*), plus increases in account payables (*apalch*, or if unavailable by $ap_t - ap_{t-1}$ from the balance sheet account), decreases in total receivables (*recch*, or if unavailable by $rect_{t-1} - rect_t$ from the balance sheet account), and decreases in total inventories (*invch*, or if unavailable by $invt_{t-1} - invt_t$ from the balance sheet account). Intuitively, an increase in outstanding payables from one period to the next increases a firm's cash positions, while increasing inventories and receivables diminish a firm's liquidity. In Compustat, the definition of cash flows vary according to the format code a firm follows in reporting flow-of-funds data: prior to 15th July, 1988, the Statement of Cash Flows format code in Computat (*scf*) was coded as either 1,2 or 3; and afterwards with format code *scf*=7. The sum of funds from operations (*fopt*) is available for cash flow statement with format code [*scf*=1,2,3]. For cash flow statement with format code [*scf*=7], *fopt* is defined as the sum of the following variables: income before extraordinary items (*ibc*), depreciation and amortization (*dpc*), deferred taxes (*txdc*), equity in net loss/earnings (*esubc*), sale of property, plant and equipment, and investments-gain/loss (*sppiv*), and funds from operations-other (*fopo*).

B.2.2 BIS-based Measures of Capital Inflows

We provide further details on three measures of gross debt inflows introduced in the robustness section that are constructed from the cross-border bank positions gathered by the BIS.

The first measure is based on the Locational Banking Statistics (LBSR) data—compiled on a residency basis as done in the BOP—and use for each counterparty country c the available BIS's exchange rate- and break-adjusted change[109] (expressed in terms of GDP) in cross-border claims (XBC) in the form of loans—abstracting from debt securities, derivatives or other debt holdings made by banks—of internationally active banks located in all reporting countries vis-à-vis all borrowing sectors (both private and public sectors).

The second measure focuses instead on cross-border banking inflows to the private sector only (banks and non-bank private sector). Break- and exchange rate-adjusted flows to all counterparty sectors, as the first measure, are directly reported in LBS, but a focus on private sector flows is less straightforward. Up until recently, the LBS data provides only a breakdown of counterparties into banks and non-banks (corporate and government sectors). In a nutshell, and following the procedures in Avdjiev et al. (2018) (see their Appendix B.3), we first adjust the outstanding stocks for break-in-series, and then use the more granular sectoral split information contained in the BIS's CBS data to isolate the outstanding stocks of the non-bank private sector in LBS data. We take advantage of the fact that LBS contains a currency breakdown and compute exchange rate-adjusted flows in line with BIS's method.

The third measure relies on a broader definition of banking inflows that accounts for the credit foreign-owned banks (subsidiaries or branches of a bank headquartered overseas) residing in recipient countries extend locally to other banks or firms. Absent from the residence-based perspective (the BOP and LBSR datasets), local banking of foreign-owned affiliates is nonetheless captured by the BIS's Consolidated Banking Statistics (CBS). We thus draw on the CBS data to construct for each recipient country c an aggregate and estimated measure of bank inflows as the break- and exchange rate-adjusted changes in total foreign claims (FC) in all instruments from all reporting countries to the bank and

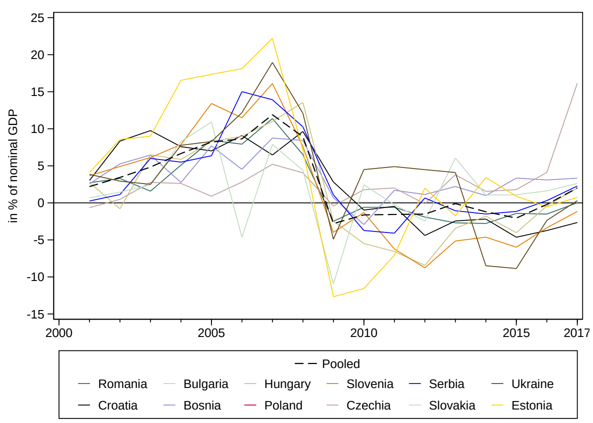
[109]The BIS International Banking Statistics data are converted and reported in U.S. dollars, thus simple changes in amounts outstanding may reflect exchange rate-related valuation effects. Fortunately, the availability of a currency breakdown in the LBS data enables the BIS to calculate exchange rate-adjusted flows by first converting claims into their original currency using end-of-period exchange rates, and then converting the difference in amounts outstanding into a U.S. dollar-equivalent change using average period exchange rates (BIS, 2019). Flows are also adjusted for breaks-in-series arising from changes in methodology, reporting practice or reporting population.

non-bank private counterparty sectors (see e.g., Houston et al., 2012; Karolyi et al., 2018). Foreign claims (FC) are defined as the sum of cross-border claims (XBC) and local claims of foreign-affiliated banks in local ($LCLC$) or foreign currency ($LCFC$). In the CBS data on an immediate counterparty basis, foreign claims are broken down into two components: a) international claims (INT) on a borrower country c which includes all cross-border claims in all currencies booked by the reporting banks' offices worldwide plus only the part of local claims denominated in foreign currency (i.e., $INT{=}XBC{+}LCFC$), and b) any locally-extended claims denominated in the domestic currency of country c ($LCLC$). While consolidation in the CBS data enables to include the lending of banks' foreign affiliates, intra-group cross-border claims are net out, which avoids double-counting. Since there is no currency breakdown available, the CBS data only report outstanding claims unadjusted to breaks-in-series and valuation changes induced by exchange rate movements. We adjust $LCLC$ and INT accordingly using the procedures described in Amiti et al. (2019) and Cerutti (2015).

B.3 Sample Description and Summary statistics

Figure B.I. Non-Residents Total Debt Inflows to the Private Sector, Sample of Emerging Economies, by Country (in % of nominal GDP)

(a) $CF_{c,t}$



(b) $CF_{c,MAt,t\text{-}2}$

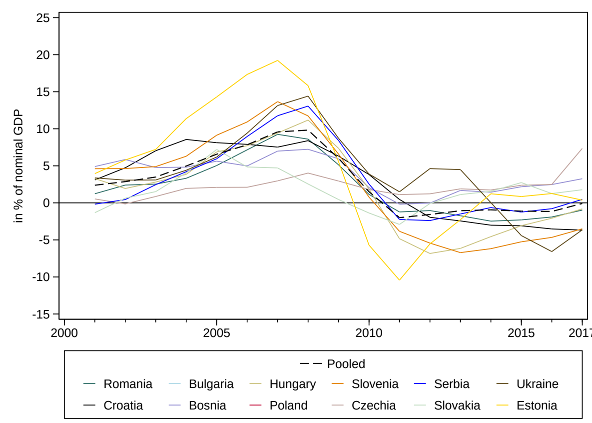
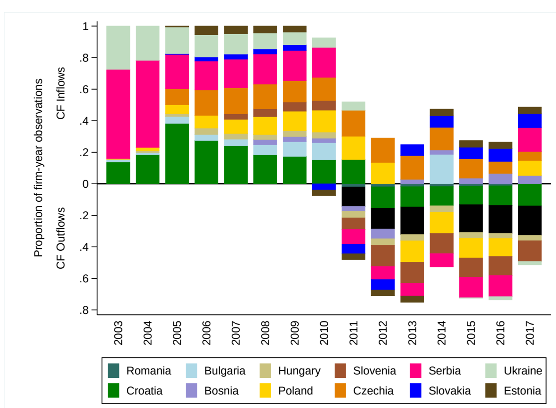


Figure B.II. Breakdown of Observations in Sample A by Country and by the Direction of Debt Inflows

(a) $CF_{c,t}$



(b) $CF_{c,MAt,t\text{-}2}$

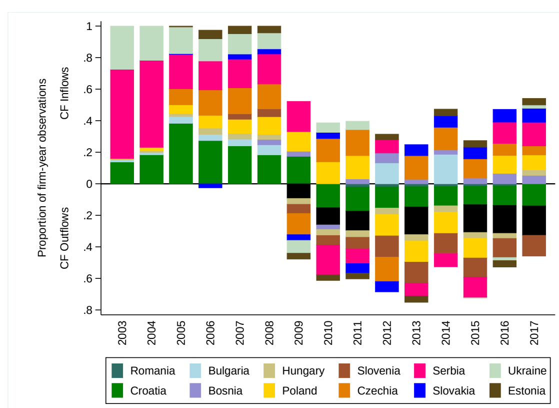


Table B.1. Samples Description: Breakdown by Country

Samples	**Sample A** Intensive		**Sample B** Intensive + Extensive		**Sample C** Intensive + Extensive		**Sample D** TFP dummy	
Country	# obs.	# firm	# obs.	# firm	# obs.	# firm	# obs.	# firm
BA	27799 (3.36%)	7654 (4.17%)	31961 (3.13%)	8659 (3.89%)	38613 (2.39%)	10097 (3.07%)	58791 (1.77%)	15838 (2.12%)
BG	105575 (12.78%)	24681 (13.45%)	133143 (13.02%)	30360 (13.65%)	239504 (14.82%)	51269 (15.61%)	348467 (10.52%)	88435 (11.84%)
CZ	107169 (12.97%)	24052 (13.11%)	141826 (13.87%)	30546 (13.74%)	261447 (16.18%)	48847 (14.88%)	332456 (10.03%)	68028 (9.11%)
EE	32202 (3.90%)	7016 (3.82%)	37505 (3.67%)	8044 (3.62%)	52680 (3.26%)	10554 (3.21%)	77614 (2.34%)	17439 (2.33%)
HR	134590 (16.29%)	26563 (14.47%)	160034 (15.65%)	30549 (13.74%)	220319 (13.63%)	38066 (11.59%)	327095 (9.87%)	60828 (8.14%)
HU	29856 (3.61%)	6019 (3.28%)	39180 (3.83%)	7692 (3.46%)	61113 (3.78%)	10963 (3.34%)	81629 (2.46%)	16213 (2.17%)
PL	96769 (11.71%)	20940 (11.41%)	118293 (11.57%)	25975 (11.68%)	155561 (9.63%)	32920 (10.03%)	197801 (5.97%)	46390 (6.21%)
RO	7386 (0.89%)	1883 (1.03%)	8468 (0.83%)	2132 (0.96%)	13236 (0.82%)	3158 (0.96%)	938187 (28.32%)	204599 (27.39%)
RS	122506 (14.83%)	25904 (14.12%)	146496 (14.33%)	29416 (13.23%)	176398 (10.91%)	32743 (9.97%)	297334 (8.97%)	59282 (7.93%)
SI	73182 (8.86%)	15749 (8.58%)	80562 (7.88%)	17213 (7.74%)	96140 (5.95%)	19966 (6.08%)	148235 (4.47%)	32498 (4.35%)
SK	46389 (5.61%)	11302 (6.16%)	59728 (5.84%)	14292 (6.43%)	113947 (7.05%)	25002 (7.61%)	148295 (4.48%)	37043 (4.96%)
UA	42794 (5.18%)	11758 (6.41%)	65077 (6.37%)	17498 (7.87%)	187226 (11.58%)	44787 (13.64%)	357365 (10.79%)	100504 (13.45%)
Total	826217 (100%)	183521 (100%)	1022273 (100%)	222376 (100%)	1616184 (100%)	328372 (100%)	3313269 (100%)	747097 (100%)

Note: The table presents the breakdown of firm-year observations and the number of unique firms by country, for the various final samples used in our analysis (see Appendix B.1.6 for the full definitions of the different samples). The country codes are BA (Bosnia-Herzegovina), BG (Bulgaria), CZ (Czech Republic), EE (Estonia), HR (Croatia), HU (Hungary), PL (Poland), RO (Romania), RS (Serbia), SI (Slovenia), SK (Slovakia) and UA (Ukraine).

Table B.2. Samples Description: Breakdown by Year

Samples	**Sample A** Intensive		**Sample B** Intensive + Extensive		**Sample C** Intensive + Extensive		**Sample D** TFP dummy	
Year	# obs.	in %	# obs.	in %	# obs.	in %	# obs.	in %
2003	6377	0.77%	9139	0.89%	15399	0.95%	79564	2.40%
2004	9819	1.19%	14400	1.41%	22232	1.38%	86193	2.60%
2005	29731	3.60%	39426	3.86%	66863	4.14%	154618	4.67%
2006	41016	4.96%	53170	5.20%	84962	5.26%	188824	5.70%
2007	49906	6.04%	63208	6.18%	98946	6.12%	212586	6.42%
2008	60173	7.28%	77306	7.56%	116700	7.22%	238029	7.18%
2009	63242	7.65%	80727	7.90%	125195	7.75%	252125	7.61%
2010	64478	7.80%	78619	7.69%	128707	7.96%	260952	7.88%
2011	62314	7.54%	76113	7.45%	128461	7.95%	250649	7.57%
2012	69306	8.39%	82901	8.11%	124546	7.71%	242130	7.31%
2013	71050	8.60%	85243	8.34%	133694	8.27%	250796	7.57%
2014	73124	8.85%	87902	8.60%	138821	8.59%	265418	8.01%
2015	79452	9.62%	95834	9.37%	150218	9.29%	291842	8.81%
2016	79304	9.60%	97631	9.55%	152745	9.45%	288811	8.72%
2017	66925	8.10%	80654	7.89%	128695	7.96%	250732	7.57%
Total	826217	100%	1022273	100%	1616184	100%	3313269	100%

Note: The table presents the year breakdown of firm-year observations, for the various final samples used in our analysis (see Appendix B.1.6 for the full definitions of the different samples).

Table B.3. Samples Description: Breakdown by Sector (proportion of firm-year obs.)

Letter (NACE 2dig)		Description	Sample A	Sample B	Sample C	Sample D
C		**MANUFACTURING**	**27.87%**	**27.04%**	**24.72%**	**22.55%**
	10	Manufacture of food products	4.27%	3.99%	3.24%	3.01%
	11	Manufacture of beverages	0.57%	0.54%	0.45%	0.35%
	13	Manufacture of textiles	0.61%	0.60%	0.53%	0.53%
	14	Manufacture of wearing apparel	1.08%	1.06%	1.07%	1.30%
	15	Manufacture of leather and related products	0.30%	0.30%	0.29%	0.40%
	16	Manufacture of wood and of products of wood and cork, [...]	1.87%	1.76%	1.48%	1.66%
	17	Manufacture of paper and paper products	0.82%	0.76%	0.63%	0.53%
	18	Printing and reproduction of recorded media	1.27%	1.24%	1.10%	1.06%
	20	Manufacture of chemicals and chemical products	0.84%	0.82%	0.74%	0.66%
	22	Manufacture of rubber and plastic products	2.34%	2.22%	1.90%	1.60%
	23	Manufacture of other non-metallic mineral products	1.47%	1.44%	1.37%	1.17%
	24	Manufacture of basic metals	0.54%	0.51%	0.43%	0.34%
	25	Manufacture of fabricated metal products, except machinery and equipment	4.70%	4.57%	4.16%	3.52%
	26	Manufacture of computer, electronic and optical products	0.78%	0.80%	0.88%	0.73%
	27	Manufacture of electrical equipment	1.03%	1.04%	1.06%	0.81%
	28	Manufacture of machinery and equipment n.e.c.	1.91%	1.92%	1.89%	1.50%
	29	Manufacture of motor vehicles, trailers and semi-trailers	0.50%	0.51%	0.48%	0.39%
	30	Manufacture of other transport equipment	0.22%	0.23%	0.22%	0.20%
	31	Manufacture of furniture	1.24%	1.16%	0.98%	1.06%
	32	Other manufacturing	0.64%	0.62%	0.63%	0.61%
	33	Repair and installation of machinery and equipment	0.87%	0.95%	1.19%	1.09%
F		**CONSTRUCTION**	**10.20%**	**10.63%**	**10.91%**	**11.09%**
	41	Construction of buildings	3.84%	4.06%	4.28%	4.42%
	42	Civil engineering	1.78%	1.83%	1.76%	1.47%
	43	Specialised construction activities	4.58%	4.74%	4.87%	5.21%
G		**WHOLESALE AND RETAIL TRADE; REPAIR**	**37.90%**	**37.51%**	**36.46%**	**35.90%**
	45	Wholesale and retail trade and repair of motor vehicles and motorcycles	4.64%	4.42%	3.90%	3.94%
	46	Wholesale trade, except of motor vehicles and motorcycles	23.41%	23.25%	22.37%	19.20%
	47	Retail trade, except of motor vehicles and motorcycles	9.85%	9.84%	10.20%	12.77%
H		**TRANSPORTATION AND STORAGE**	**8.24%**	**8.01%**	**7.38%**	**7.17%**
	49	Land transport and transport via pipelines	6.63%	6.34%	5.42%	5.57%
	50	Water transport	0.12%	0.12%	0.10%	0.08%
	51	Air transport	0.04%	0.04%	0.05%	0.04%
	52	Warehousing and support activities for transportation	1.44%	1.52%	1.81%	1.49%
I		**ACCOMMODATION AND FOOD SERVICE ACTIVITIES**	**3.05%**	**2.96%**	**2.92%**	**3.33%**
	55	Accommodation	1.45%	1.35%	1.27%	1.26%
	56	Food and beverage service activities	1.60%	1.61%	1.66%	2.06%
J		**INFORMATION AND COMMUNICATION**	**2.67%**	**2.95%**	**3.91%**	**4.32%**
	58	Publishing activities	0.51%	0.56%	0.74%	0.85%
	59	Motion picture, video and television programme production, [...]	0.22%	0.25%	0.29%	0.32%
	60	Programming and broadcasting activities	0.17%	0.19%	0.23%	0.23%
	61	Telecommunications	0.28%	0.29%	0.35%	0.48%
	62	Computer programming, consultancy and related activities	1.31%	1.47%	1.98%	2.07%
	63	Information service activities	0.17%	0.20%	0.32%	0.35%
M		**PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES**	**6.48%**	**7.12%**	**9.31%**	**10.85%**
	69	Legal and accounting activities	1.41%	1.52%	1.93%	2.53%
	70	Activities of head offices; management consultancy activities	1.16%	1.26%	1.51%	1.84%
	71	Architectural and engineering activities; technical testing and analysis	2.41%	2.67%	3.60%	3.94%
	73	Advertising and market research	0.86%	0.98%	1.31%	1.36%
	74	Other professional, scientific and technical activities	0.45%	0.51%	0.75%	0.87%
	75	Veterinary activities	0.18%	0.19%	0.20%	0.30%
N		**ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES**	**2.89%**	**3.06%**	**3.58%**	**3.54%**
	77	Rental and leasing activities	0.66%	0.65%	0.67%	0.52%
	78	Employment activities	0.16%	0.19%	0.22%	0.23%
	79	Travel agency, tour operator and other reservation service	0.64%	0.65%	0.70%	0.69%
	80	Security and investigation activities	0.48%	0.52%	0.61%	0.58%
	81	Services to buildings and landscape activities	0.58%	0.62%	0.79%	0.74%
	82	Office administrative, office support and other business support activities	0.38%	0.43%	0.59%	0.78%
S		**OTHER SERVICE ACTIVITIES**	**0.70%**	**0.72%**	**0.81%**	**1.24%**
	95	Repair of computers and personal and household goods	0.30%	0.33%	0.37%	0.58%
	96	Other personal service activities	0.39%	0.40%	0.44%	0.67%
		Total number of firm-year observations	**826217**	**1022273**	**1616184**	**3313269**

Note: The table presents the sectoral breakdown of firm-year observations, for the various final samples used in our analysis (see Appendix B.1.6 for the samples' definitions). The following sectors are excluded: Agriculture (1-3), Mining and quarrying (5-9), Tobacco (12), Pharma (21), Utilities (35-9), Postal services (53), Financial and insurance (64-6), Real estate (68), Scientific R&D (72), Public administration (84), Education and Health services (85-8), Arts and recreation (90-3), Households as employers (97-8), Extraterritorial organizations (99).

Table B.4. Samples Description: Breakdown by Size Classes

	Sample A Intensive		**Sample B** Intensive + Extensive		**Sample C** Intensive + Extensive		**Sample D** TFP dummy	
Size Class	# obs.	# firms	# obs.	# firms	# obs.	# firms	# obs.	# firms
SME	738777 (89.4%)	166926 (91.0%)	918333 (89.8%)	202976 (91.3%)	1470497 (91.0%)	303702 (92.5%)	3098023 (93.5%)	710318 (95.1%)
Micro	18370 (2.2%)	5782 (3.2%)	25157 (2.5%)	7635 (3.4%)	57468 (3.6%)	16161 (4.9%)	465476 (14.0%)	162172 (21.7%)
Small	502010 (60.8%)	119719 (65.2%)	631155 (61.7%)	146822 (66.0%)	1040072 (64.4%)	224727 (68.4%)	2094827 (63.2%)	461138 (61.7%)
Medium	218397 (26.4%)	41425 (22.6%)	262021 (25.6%)	48519 (21.8%)	372957 (23.1%)	62814 (19.1%)	537720 (16.2%)	87008 (11.6%)
Large	87440 (10.6%)	16595 (9.0%)	103940 (10.2%)	19400 (8.7%)	145687 (9.0%)	24670 (7.5%)	215246 (6.5%)	36779 (4.9%)
All firms	826217 (100%)	183521 (100%)	1022273 (100%)	222376 (100%)	1616184 (100%)	328372 (100%)	3313269 (100%)	747097 (100%)

Note: The table presents the breakdown of firm-year observations by firm size class, for the various final samples used in our analysis (see Appendix B.1.6 for the full definitions of the different samples). We define *SMEs* as firms with less than 250 employees *or* a maximum turnover of $15 million *or* total assets less than $15 million. Within SMEs, *micro* firms have fewer than 10 employees or revenues/assets less than $100,000; *small* firms have fewer than 50 employees or revenues/assets of up to $3 million; *medium* firms have less than 250 employees *or* a maximum revenues/assets of $15 million. Firms are defined as *large* if they have either 250 or more persons employed, or revenues/assets over $15 million.

Table B.5. Summary Statistics, Breakdown by Size Classes, Selected Firm-level Variables

	Sample A Intensive margin						**Sample B** Intensive + Extensive margins excluding years a firm stays unlevered					
				SME						SME		
	All	Large	SME	Micro	Small	Medium	All	Large	SME	Micro	Small	Medium
Nb. of firm-year obs. (in %)	826217 (100%)	87440 (10.58%)	738777 (89.42%)	18370 (2.22%)	502010 (60.76%)	218397 (26.43%)	1022273 (100%)	103940 (10.17%)	918333 (89.83%)	25157 (2.46%)	631155 (61.74%)	262021 (25.63%)
Nb. of distinct firms (in %)	183521 (100%)	16595 (9.04%)	166926 (90.96%)	5782 (3.15%)	119719 (65.23%)	41425 (22.57%)	222376 (100%)	19400 (8.72%)	202976 (91.28%)	7635 (3.43%)	146822 (66.02%)	48519 (21.82%)
% of extensive margin changes	0%	0%	0%	0%	0%	0%	16.59%	14.26%	16.85%	21.50%	17.46%	14.93%
TFP (in log)	2.19	2.67	2.13	1.44	2.03	2.42	2.18	2.67	2.13	1.45	2.03	2.42
Labor Productivity (in log)	1.32	1.50	1.30	1.00	1.27	1.39	1.34	1.50	1.32	1.02	1.29	1.40
Real assets (in th. dollars)	7296.9	53844.6	1787.6	83.8	699.6	4431.9	6849.7	52456.0	1687.8	83.2	667.8	4298.9
Nb. of employees	70.67	487.28	26.69	3.25	11.87	65.81	67.50	480.58	26.10	3.32	11.82	65.76
Age	16.46	21.66	15.83	13.74	15.02	17.79	16.21	21.43	15.60	13.60	14.81	17.63
Profitability (ratio)	0.058	0.049	0.060	0.047	0.061	0.058	0.064	0.053	0.065	0.055	0.067	0.063
Sales growth	0.007	0.008	0.007	0.007	0.006	0.007	0.007	0.008	0.006	0.007	0.006	0.007
Total Debt ratio	0.60	0.60	0.60	0.63	0.61	0.59	0.58	0.58	0.58	0.60	0.59	0.57
ST Debt ratio	0.45	0.47	0.45	0.48	0.45	0.45	0.45	0.46	0.45	0.47	0.45	0.44
LT Debt ratio	0.15	0.13	0.15	0.15	0.16	0.14	0.13	0.12	0.13	0.13	0.14	0.13
Financial Debt ratio	0.23	0.22	0.23	0.28	0.24	0.22	0.20	0.19	0.20	0.23	0.20	0.19
% obs. with Fin. Debt Ratio=0	0%	0%	0%	0%	0%	0%	8.56%	7.64%	8.67%	11.06%	8.92%	7.84%
% obs. with Fin. Debt Ratio≤2%	8.30%	9.64%	8.14%	6.56%	7.65%	9.41%	17.82%	19.16%	17.67%	18.11%	17.30%	18.53%
△ ln(Fin. Debt)	0.82%	5.72%	0.24%	-2.57%	-0.93%	3.18%	0.37%	5.54%	-0.24%	-3.51%	-1.47%	2.93%
DHS Fin. Debt Growth	-0.18%	4.33%	-0.72%	-3.93%	-1.83%	2.12%	-1.63%	1.47%	-1.98%	-5.07%	-2.70%	0.07%
△ Fin. Debt / Total Assets	1.23%	1.90%	1.15%	0.61%	0.99%	1.55%	1.35%	1.74%	1.31%	1.09%	1.23%	1.51%
△ ln(Total Debt)	3.70%	7.14%	3.29%	2.67%	2.55%	5.04%	3.63%	7.09%	3.23%	2.24%	2.49%	5.04%

Table B.5. (*continued*)

	Sample C Intensive + Extensive margins including years a firm stays unlevered						**Sample D** Not directly used in regressions in which the TFP dummy's cut-offs are computed					
				SME						SME		
	All	Large	SME	Micro	Small	Medium	All	Large	SME	Micro	Small	Medium
Nb. of firm-year obs.	1616184	145687	1470497	57468	1040072	372957	3313269	215246	3098023	465476	2094827	537720
(in %)	(100%)	(9.01%)	(90.99%)	(3.56%)	(64.35%)	(23.08%)	(100%)	(6.50%)	(93.50%)	(14.05%)	(63.23%)	(16.23%)
Nb. of distinct firms	328372	24670	303702	16161	224727	62814	747097	36779	710318	162172	461138	87008
(in %)	(100%)	(7.51%)	(92.49%)	(4.92%)	(68.44%)	(19.13%)	(100%)	(4.92%)	(95.08%)	(21.71%)	(61.72%)	(11.65%)
% of extensive margin changes	11.58%	10.97%	11.64%	11.18%	11.82%	11.24%	n.a.					
TFP (in log)	2.15	2.68	2.10	1.49	2.03	2.38	2.09	2.63	2.06	1.64	2.07	2.35
Labor Productivity (in log)	1.35	1.49	1.34	1.12	1.33	1.39	1.38	1.46	1.37	1.24	1.40	1.39
Real assets (in th. dollars)	5926.2	51163.2	1444.5	80.0	590.6	4035.9	4115.0	48597.2	1024.4	48.7	514.6	3855.3
Nb. of employees	59.01	456.10	24.37	3.85	11.76	65.43	44.03	454.14	19.36	3.23	11.52	67.10
Age	15.71	20.92	15.18	13.18	14.48	17.35	14.96	20.85	14.53	12.69	14.26	16.97
Profitability (ratio)	0.076	0.062	0.078	0.072	0.080	0.072	0.088	0.061	0.090	0.118	0.089	0.072
Sales growth	0.006	0.009	0.006	0.005	0.005	0.007	0.005	0.010	0.005	0.004	0.004	0.006
Total Debt ratio	0.52	0.55	0.52	0.47	0.52	0.52	0.53	0.55	0.53	0.46	0.54	0.54
ST Debt ratio	0.42	0.44	0.42	0.39	0.42	0.42	0.43	0.44	0.43	0.38	0.43	0.43
LT Debt ratio	0.10	0.10	0.10	0.08	0.10	0.10	0.10	0.11	0.10	0.08	0.11	0.11
Financial Debt ratio	0.13	0.14	0.12	0.10	0.12	0.13	0.11	0.14	0.11	0.07	0.11	0.13
% obs. with Fin. Debt Ratio=0	41.41%	33.56%	42.19%	59.95%	43.88%	34.75%	38.63%	33.98%	38.95%	48.49%	38.09%	34.07%
% obs. with Fin. Debt Ratio≤2%	47.46%	42.04%	47.99%	63.19%	49.14%	42.44%	42.59%	41.84%	42.64%	50.09%	41.53%	40.49%
△ ln(Fin. Debt)	-0.05%	3.26%	-0.38%	-1.32%	-1.02%	1.54%	0.20%	5.00%	-0.37%	-3.50%	-1.26%	2.76%
DHS Fin. Debt Growth	-1.23%	0.91%	-1.44%	-2.82%	-1.85%	-0.10%	-3.89%	0.47%	-4.38%	-6.58%	-4.98%	-2.11%
△ Fin. Debt / Total Assets	0.87%	1.24%	0.83%	0.50%	0.77%	1.07%	0.72%	1.19%	0.67%	0.37%	0.65%	0.94%
△ ln(Total Debt)	3.08%	6.53%	2.73%	1.16%	2.08%	4.78%	5.16%	6.86%	5.04%	4.18%	4.94%	6.13%

Note: The table reports averages of some firm-level variables across firm size categories, for the various final samples used in our analysis (see Appendix B.1.6 for the full definitions of the different samples). We define *SMEs* as firms with less than 250 employees *or* a maximum turnover of \$15 million *or* total assets less than \$15 million. Within SMEs, *micro* firms have fewer than 10 employees or revenues/assets less than \$100,000; *small* firms have fewer than 50 employees or revenues/assets of up to \$3 million; *medium* firms have less than 250 employees *or* a maximum revenues/assets of \$15 million. Firms are defined as *large* if they have either 250 or more persons employed, or revenues/assets over \$15 million.

Table B.6. Pooled Summary Statistics for the Final Regression Samples, Selected Variables

		Sample A, N=826,217 Intensive margin					**Sample B**, N=1,022,273 Intensive + Extensive margins excluding years a firm stays unlevered					**Sample C**, N=1,616,184 Intensive + Extensive margins including years a firm stays unlevered				
	Unit	Mean	S.D.	p25	p50	p75	Mean	S.D.	p25	p50	p75	Mean	S.D.	p25	p50	p75
Firm characteristics																
Total assets	Thousands 2010 $	7297	110599	31	911	3093	685	10199	28	824	2825	5926	8891	208	62	2207
Nb. employees	unit	71	744	5	14	38	68	70	5	14	38	59	581	5	12	36
Δln (Financial Debt)	%	0.82	68	-31	-3.5	28	0.37	69	-32	-3.7	28	-0.05	44	-11	0	0
Δ Financial Debt/Total Assets	% Assets	1.2	11	-4.7	-0.46	4.8	1.3	11	-4.7	-0.33	5	0.87	8.7	-2	0	0.62
Δln (Total Debt)	%	3.7	38	-15	1.2	21	3.6	39	-15	1.2	22	3.1	45	-18	1.1	24
TFP	log	2.2	0.92	1.6	2.1	2.7	2.2	0.95	1.6	2.1	2.7	2.1	1	1.5	2.1	2.8
Labor Productivity	log	1.3	0.88	0.68	1.1	1.7	1.3	0.9	0.67	1.1	1.7	1.3	0.94	0.64	1.1	1.7
Profitability	% Assets	0.058	0.11	0.007	0.034	0.091	0.064	0.12	0.008	0.037	0.1	0.076	0.19	0.008	0.044	0.12
Cash-Flow Ratio	% Assets	0.11	0.11	0.041	0.086	0.16	0.12	0.12	0.042	0.09	0.17	0.13	0.14	0.043	0.096	0.18
Fixed Assets Ratio	% Assets	0.35	0.25	0.13	0.32	0.54	0.34	0.25	0.11	0.3	0.53	0.31	0.26	0.081	0.25	0.49
Intangible Assets Ratio	% Assets	0.007	0.033	0	0	0.001	0.007	0.033	0	0	0.001	0.006	0.032	0	0	0
Cash Ratio	% Assets	0.086	0.13	0.009	0.034	0.1	0.097	0.14	0.01	0.039	0.12	0.14	0.19	0.015	0.061	0.19
Debt Overhang Ratio	% Assets	0.22	0.51	0.041	0.1	0.24	0.27	0.71	0.042	0.11	0.27	0.51	1.6	0.045	0.14	0.4
Total Debt Ratio	% Assets	0.6	0.23	0.43	0.63	0.79	0.58	0.24	0.4	0.6	0.78	0.52	0.27	0.29	0.54	0.75
Financial Debt Ratio	% Assets	0.23	0.18	0.084	0.19	0.34	0.2	0.18	0.046	0.15	0.3	0.13	0.18	0	0.035	0.21
External Financial Need	unit	0.92	0.18	0.9	0.96	0.99	0.91	0.21	0.89	0.96	0.99	0.88	0.36	0.86	0.95	0.99
Altman's Z score	unit	3.6	4.6	1.6	3.1	5	4	6.1	1.7	3.3	5.3	6.1	16	1.9	3.8	6.5
Country-level variables																
Debt inflows (BOP)	%	1.5	5.5	-1.7	0.66	3.8	1.7	5.6	-1.4	0.68	4.1	2	5.7	-1.2	0.76	4.5
Banking Inflows (BIS)	%	-0.065	4.5	-2.7	-0.65	2.1	0.046	4.6	-2.7	-0.57	2.2	0.046	4.7	-2.7	-0.65	2.2
Exchange rate change	%	2.7	1	-3.2	0	7.1	2.7	1	-3.2	0	7.1	2.9	11	-3.2	0.042	7.1
Trade-to-GDP ratio	% GDP	113	32	84	104	139	113	32	84	104	138	116	32	89	108	142
Unemployment rate	%	11	5.2	7.2	9.7	14	11	5.1	7.1	9.6	14	1	4.8	6.9	9.1	13
Consumer price change	%	3.3	4.2	0.68	2.2	4.2	3.5	4.4	0.81	2.3	4.2	3.8	5	0.68	2.3	5
Real GDP growth rate	%	2.3	3.4	0.73	2.7	4.2	2.3	3.5	0.73	2.7	4.3	2.3	3.8	0.96	2.8	4.3
Stock market returns	%	4.7	35	-15	2.9	23	5.2	36	-15	2.9	23	6.6	37	-15	3	29
Share of local banking system assets held by foreign-owned banks	% Banking assets	73	18	66	77	86	73	18	66	77	85	72	18	63	77	84
Corporate lending rate	%	6.7	3.4	4.5	6.2	7.4	6.9	3.6	4.5	6.2	7.9	7.4	4.3	4.4	6.5	8.5
Bank NPLs	% Total gross loans	9.6	6.3	4.8	7.4	15	9.5	6.4	4.8	6.2	15	9.4	6.5	4.7	5.8	15

Note: The table reports pooled summary statistics for seleted variables and for the final samples of firms used in the analysis (see Appendix B.1.6 for the full definitions of the different samples). Of note, banks' NPL data come from the World Bank's Global Financial Development (GFD) database; data on interest rates on loans to non-financial corporations come from a variety of sources (the ECB, the Global Financial Database, and national central banks), following House et al. (2020). The other variables are introduced and defined in the main text.

Table B.7. Coverage and Size Distribution of our Final Samples (ratios)

Sample D: largest final sample where TFP cut-offs are computed

	Coverage in ORBIS relative to Official						Firm Size Distribution			
	ORBIS/Official						ORBIS		Official	
	Turnover			Employment			Turnover		Turnover	
	Total	SME	Large	Total	SME	Large	SME	Large	SME	Large
BA	0.53	0.54	0.57	0.46	0.48	0.53	0.76	0.24	0.76	0.24
BG	0.57	0.49	0.77	0.55	0.47	0.75	0.63	0.37	0.74	0.26
CZ	0.57	0.45	0.74	0.57	0.43	0.79	0.47	0.53	0.61	0.39
EE	0.36	0.53	0.53	0.32	0.39	0.42	0.73	0.27	0.77	0.23
HR	0.74	0.68	0.81	0.58	0.51	0.72	0.62	0.38	0.65	0.35
HU	0.51	0.37	0.70	0.32	0.17	0.66	0.45	0.55	0.61	0.39
PL	0.32	0.26	0.43	0.16	0.10	0.29	0.49	0.51	0.62	0.38
RO	0.62	0.58	0.68	0.55	0.50	0.65	0.59	0.41	0.63	0.37
RS	0.70	0.69	0.71	0.60	0.56	0.65	0.66	0.34	0.66	0.34
SI	0.56	0.63	0.66	0.50	0.51	0.71	0.62	0.41	0.60	0.42
SK	0.48	0.54	0.43	0.41	0.40	0.51	0.61	0.39	0.57	0.43
UA	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Average	0.54	0.52	0.64	0.46	0.41	0.61	0.60	0.40	0.66	0.35

Sample B: regression sample on financial debt adjustments at both the intensive and extensive margins

	Coverage in ORBIS relative to Official						Firm Size Distribution			
	ORBIS/Official						ORBIS		Official	
	Turnover			Employment			Turnover		Turnover	
	Total	SME	Large	Total	SME	Large	SME	Large	SME	Large
BA	0.23	0.27	0.37	0.19	0.25	0.38	0.88	0.12	0.91	0.09
BG	0.25	0.24	0.49	0.24	0.22	0.49	0.73	0.31	0.83	0.19
CZ	0.31	0.24	0.43	0.32	0.23	0.50	0.47	0.53	0.61	0.39
EE	0.15	0.27	0.72	0.14	0.20	0.59	0.92	0.09	0.96	0.04
HR	0.43	0.38	0.78	0.33	0.29	0.65	0.63	0.43	0.74	0.30
HU	0.20	0.15	0.29	0.15	0.09	0.32	0.54	0.46	0.67	0.33
PL	0.17	0.14	0.25	0.08	0.05	0.17	0.53	0.51	0.67	0.36
RO	0.21	0.13	0.36	0.14	0.06	0.33	0.39	0.61	0.63	0.37
RS	0.40	0.42	0.53	0.32	0.34	0.46	0.70	0.30	0.75	0.25
SI	0.35	0.48	0.52	0.32	0.37	0.61	0.66	0.34	0.68	0.32
SK	0.18	0.23	0.18	0.17	0.18	0.26	0.75	0.25	0.70	0.30
UA	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Average	0.27	0.27	0.44	0.22	0.21	0.42	0.66	0.36	0.74	0.27

Note: This table reports on the left-hand side coverage of our final samples (Samples D and B, see Appendix B.1.6 for further details) relative to official SBS data in terms of gross output and employment. Both samples were subject to extensive cleaning and data restrictions. On the right hand-side, the table presents firm size distribution (across SME and large size categories) in terms of gross output for our final samples and the respective distribution in official SBS data. The table presents ratios that are themselves time averages from 2003 to 2017. Following Kalemli-Özcan et al. (2015), for a given country-year cell, agreggate economy percentages are computed by taking the ratio of the value of aggregated gross output produced by the firms (either all, SME or large firms only) in our final samples to official values across those sectors for which gross-output related variable is available in both data sets. A similar procedure is adopted in terms of employment. Then for each country, we take the average of these ratios over 2003-2017. The last row gives a simple average of all country cells. Regarding firm size distribution, we report for each country the 2003-2017 average share of indicated firm size category's gross output from the relevant data sources, based on sectors present in both data sets. SME includes firms with less than 250 employees. The country codes are BA (Bosnia-Herzegovina), BG (Bulgaria), CZ (Czech Republic), EE (Estonia), HR (Croatia), HU (Hungary), PL (Poland), RO (Romania), RS (Serbia), SI (Slovenia), SK (Slovakia) and UA (Ukraine, where no SBS official statistics are available). Appendix B.1.7 provides details on the construction of official SBS data.

Figure B.III. Non-Residents Total Debt Inflows to the Private Sector, Sample of Advanced Economies, by Country (in % of nominal GDP)

(a) $CF_{c,t}$ (b) $CF_{c,MAt,t\text{-}2}$

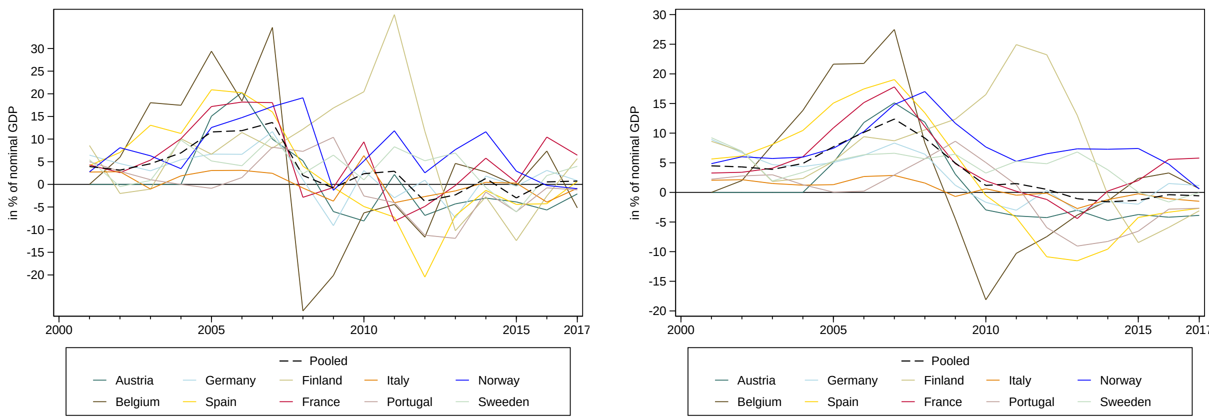


Table B.8. Samples Description: Breakdown by Country, Advanced Countries

Samples	**Sample A** Intensive		**Sample B** Intensive + Extensive		**Sample C** Intensive + Extensive		**Sample D** TFP dummy	
Country	# obs.	# firm	# obs.	# firm	# obs.	# firm	# obs.	# firm
AT	7868 (0.15%)	1627 (0.16%)	8816 (0.14%)	1724 (0.15%)	9636 (0.12%)	1804 (0.13%)	13183 (0.13%)	2803 (0.15%)
BE	50880 (0.95%)	7972 (0.77%)	56961 (0.90%)	8801 (0.75%)	78933 (0.96%)	10860 (0.76%)	90120 (0.88%)	12443 (0.67%)
DE	101117 (1.90%)	24720 (2.40%)	115912 (1.84%)	28223 (2.40%)	143313 (1.74%)	32437 (2.27%)	195405 (1.92%)	59781 (3.20%)
ES	1335572 (25.04%)	263103 (25.55%)	1495561 (23.72%)	288094 (24.55%)	1886532 (22.85%)	340156 (23.78%)	2511691 (24.66%)	448361 (24.01%)
FI	124921 (2.34%)	25682 (2.49%)	144481 (2.29%)	29211 (2.49%)	191036 (2.31%)	38243 (2.67%)	262953 (2.58%)	58147 (3.11%)
FR	1706247 (31.99%)	325175 (31.58%)	1959826 (31.08%)	359792 (30.66%)	2307344 (27.95%)	401635 (28.08%)	2736703 (26.87%)	512027 (27.42%)
IT	1213146 (22.75%)	225796 (21.93%)	1566584 (24.84%)	275189 (23.45%)	2192181 (26.55%)	351994 (24.61%)	2571054 (25.24%)	440725 (23.60%)
NO	141499 (2.65%)	26765 (2.60%)	179118 (2.84%)	32628 (2.78%)	367029 (4.45%)	55866 (3.91%)	438338 (4.30%)	68839 (3.69%)
PT	401045 (7.52%)	76724 (7.45%)	468371 (7.43%)	87115 (7.42%)	580010 (7.03%)	102074 (7.14%)	717408 (7.04%)	133528 (7.15%)
SE	251142 (4.71%)	52035 (5.05%)	310443 (4.92%)	62856 (5.36%)	500041 (6.06%)	95437 (6.67%)	648987 (6.37%)	130912 (7.01%)
Total	5333437 (100%)	1029599 (100%)	6306073 (100%)	1173633 (100%)	8256055 (100%)	1430506 (100%)	10185842 (100%)	1867566 (100%)

Note: The table presents the breakdown of firm-year observations and the number of unique firms by country, for the various final samples used in our analysis that include 10 advanced economies (see Appendix B.1.6 for the full definitions of the different samples). The country codes are AT (Austria), BE (Belgium), DE (Germany), ES (Spain), FI (Finland), FR (France), IT (Italy), NO (Norway), PT (Portugal) and SE (Sweden).

Table B.9. Samples Description: Breakdown by Year, Advanced Countries

Samples	**Sample A** Intensive		**Sample B** Intensive + Extensive		**Sample C** Intensive + Extensive		**Sample D** TFP dummy	
Year	# obs.	in %	# obs.	in %	# obs.	in %	# obs.	in %
2003	29123	0.55%	34178	0.54%	45060	0.55%	66073	0.65%
2004	71032	1.33%	82350	1.31%	110646	1.34%	129660	1.27%
2005	324300	6.08%	408098	6.47%	521481	6.32%	561955	5.52%
2006	387113	7.26%	456881	7.25%	577031	6.99%	662552	6.50%
2007	369440	6.93%	436445	6.92%	576249	6.98%	754559	7.41%
2008	373887	7.01%	452470	7.18%	592503	7.18%	781053	7.67%
2009	448084	8.40%	527863	8.37%	674892	8.17%	805357	7.91%
2010	459682	8.62%	544300	8.63%	697239	8.45%	853168	8.38%
2011	475258	8.91%	555152	8.80%	714017	8.65%	873018	8.57%
2012	482259	9.04%	555568	8.81%	716644	8.68%	883543	8.67%
2013	458647	8.60%	529346	8.39%	686348	8.31%	856624	8.41%
2014	400666	7.51%	476357	7.55%	621156	7.52%	764070	7.50%
2015	393360	7.38%	459522	7.29%	619308	7.50%	762909	7.49%
2016	366854	6.88%	444059	7.04%	605689	7.34%	760483	7.47%
2017	293732	5.51%	343484	5.45%	497792	6.03%	670818	6.59%
Total	5333437	100%	6306073	100%	8256055	100%	10185842	100%

Note: The table presents the year breakdown of firm-year observations, for the various final samples used in our analysis that include 10 advanced economies (see Appendix B.1.6 for the full definitions of the different samples).

C. Supplementary Evidence

C.1 Complementary Evidence to Section 4

Table C.1. Firm's Debt Growth and Capital Inflows at Different Lags, All Firms

Dependent variable: **$\Delta\ln(y_{i,t})$, y=Financial Debt**	**all lags included**	**lags included separately**			**lags in MA form**	
	$\sum_{q=0}^{2} CF_{\text{t-q}}$	CF_{t}	$CF_{\text{t-1}}$	$CF_{\text{t-2}}$	$CF_{\text{MAt,t-1}}$	$CF_{\text{MAt,t-2}}$
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,t}}$	-0.032 (-0.67)	-0.127*** (-3.00)				
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,t-1}}$	-0.116** (-2.23)		-0.202*** (-5.16)			
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,t-2}}$	-0.117*** (-2.67)			-0.185*** (-5.09)		
$D^{TFP}_{i,t-1} \times \text{CF}_{\text{c,MA}}$					-0.217*** (-4.59)	-0.276*** (-5.42)
◇ H_0: $\Sigma\ D^{TFP}_{i,t-1} \times \text{CF}_{\text{t-q}}$=0 (t-stat)	-0.265*** (-5.05)					
◇ Exclusion test (p-value)	11.010*** (0.000)					
Firm Controls$_{\text{i,t-1}}$	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s\times t$, $c\times t$, $c\times s$	yes	yes	yes	yes	yes	yes
Observations	826217	826217	826217	826217	826217	826217
Number of firms	183521	183521	183521	183521	183521	183521
Within Adj. R^2	0.024	0.024	0.024	0.024	0.024	0.024

Note: This table reports the results of estimating $\Delta\ln(y_{i,t})=\alpha+\Psi+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$, where Ψ is equal to $\sum_{q=0}^{2}\beta_q\big(D^{TFP}_{i,t-1}\times CF_{c,t-q}\big)$ when we include lags simultaneously, equal to $\beta\big(D^{TFP}_{i,t-1}\times CF_{c,t-q}\big)$ when lags are included separately with q=0,1,2, or equal to $\beta\big(CF_{c,MA,t,t-h}\times D^{TFP}_{i,t-1}\big)$ when lags are included in MA form with h=1,2. One observation is one firm-year between 2003 and 2017 (unbalanced panel), and the sample includes all firms. Singleton are dropped. The dependent variable is the log-difference of outstanding financial (interest bearing) debt of firm i in year t. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in $t-1$ and $t-2$, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and enters the regression at different timing lags. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.2. Intensive and Extensive Margin Changes, Alternative TFP Cut-offs

Margin Changes:	**Intensive + Extensive** with {entry,exit} $\in$ Extensive					
Sample:	**Baseline: All firms** excluding years a firm stays unlevered			**Alternative: All firms** including years a firm stays unlevered		
TFP cutoff:	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$						
$D^{TFP}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.459***	-0.681***	-0.834***	-0.297***	-0.396***	-0.471***
	(-6.80)	(-7.57)	(-7.06)	(-6.16)	(-6.24)	(-6.08)
Observations	1022273	702332	501789	1616184	1124011	814274
% Extensive changes	16.6%	16.5%	16.6%	11.6%	11.6%	11.6%
% Stay Unlevered	0%	0%	0%	35.4%	35.9%	36.6%
Number of firms	222376	169762	128234	328372	255767	196589
Within Adj. R^2	0.017	0.017	0.017	0.010	0.009	0.010
Dep. var. avg;p50 (in %)	-1.6;-4	-1.5;-3.8	-1.5;-3.6	-1.2;0	-1.2;0	-1.2;0
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$						
$D^{TFP}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.063***	-0.084***	-0.111***	-0.034***	-0.041***	-0.052***
	(-7.38)	(-7.58)	(-8.14)	(-5.83)	(-5.39)	(-5.79)
Observations	1022273	702332	501789	1616184	1124011	814274
% Extensive changes	16.6%	16.5%	16.6%	11.6%	11.6%	11.6%
% Stay Unlevered	0%	0%	0%	35.4%	35.9%	36.6%
Number of firms	222376	169762	128234	328372	255767	196589
Within Adj. R^2	0.047	0.047	0.047	0.025	0.024	0.025
Dep. var. avg;p50 (in %)	1.4;-0.3	1.4;-0.3	1.4;-0.3	0.9;0	0.9;0	0.9;0
Firm $\text{Controls}_{i,t-1}$	yes	yes	yes	yes	yes	yes
Macro $\text{Controls}_{c,t-1}$	no	no	no	no	no	no
Firm FE	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes
Country-Industry FE	yes	yes	yes	yes	yes	yes
Country-Year FE	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi=\alpha+\beta\big(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\big)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. The dependent variable Ψ is defined in Panel A as the DHS mid-point growth rate in the outstanding financial (interest bearing) debt y of firm i in year t, while in Panel B, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The right part of the table (i.e., columns 4-6) shows results based on an alternative sample in which the dependent variable Ψ is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0, thus it includes firms in years they stay unlevered. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using either the median (p50) log-TFP, or the lower and upper thirds (p33-p66), or quartiles (p25-p75) of the TFP distributions at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.3. Intensive and Extensive Margin Changes for SMEs and Large Firms

Firm Samples:	SME			Large		
Margin Changes:	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dep. var.: $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$						
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-0.498***	-0.499***	-0.255***	-0.407**	-0.596***	-0.236
	(-6.97)	(-8.16)	(-4.09)	(-2.04)	(-3.53)	(-1.35)
Observations	918248	820108	826265	103278	93767	95034
Intensive changes	763527	754087	755622	88588	87835	88019
Entrants	75143	66021	0	6814	5932	0
Exiters	79578	0	70643	7876	0	7015
Number of firms	202965	184219	185945	19296	17766	17981
Within Adj. R^2	0.018	0.043	0.006	0.010	0.025	0.005
Dep. var. avg;p50 (in %)	-2;-4.7	15.3;0	-18.2;-8.9	1.5;0	16.7;2.2	-11;-1.7
Panel B. Dep. var.: $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$						
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-0.065***	-0.074***	-0.045***	-0.057***	-0.069***	-0.038*
	(-7.22)	(-7.97)	(-5.14)	(-2.62)	(-3.08)	(-1.72)
Observations	918248	820108	826265	103278	93767	95034
Intensive changes	763527	754087	755622	88588	87835	88019
Entrants	75143	66021	0	6814	5932	0
Exiters	79578	0	70643	7876	0	7015
Number of firms	202965	184219	185945	19296	17766	17981
Within Adj. R^2	0.050	0.061	0.035	0.030	0.036	0.025
Dep. var. avg;p50 (in %)	1.3;-0.4	2;0	0.5;-1	1.7;0	2.3;0.1	1.4;0
Firm $\text{Controls}_{\text{i,t-1}}$	yes	yes	yes	yes	yes	yes
Fixed Effects: i,$s\times t$,$c\times t$,$c\times s$	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\left(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}\right){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$. The dependent variable Ψ is defined in Panel A as the DHS mid-point growth rate in the outstanding financial (interest bearing) debt y of firm i in year t, while in Panel B, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t{-}2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.4. Intensive and Extensive Margin Changes, Including Years a Firm Stays Unlevered

Firm Samples:	SME				Large			
Margin Changes:	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}	Extensive {entry,exit}	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}	Extensive {entry,exit}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.309***	-0.267***	-0.170***		-0.275*	-0.329***	-0.191	
	(-6.14)	(-6.48)	(-3.90)		(-1.84)	(-2.62)	(-1.44)	
Observations	1470447	1372799	1378659		145198	135942	137137	
Intensive changes	767281	763373	763470		89105	88811	88868	
Entrants	82765	80520	0		7381	7163	0	
Exiters	88460	0	86243		8543	0	8329	
Stay Unlevered	531941	528906	528946		40169	39968	39940	
Number of firms	303695	294443	294629		24610	23963	23996	
Within Adj. R^2	0.011	0.018	0.006		0.007	0.011	0.005	
Dep. var. avg;p50 (in %)	-1.4;0	11.1;0	-13.2;0		0.9;0	13.2;0	-9.5;0	
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.034***	-0.036***	-0.022***	-0.014***	-0.038**	-0.046***	-0.025	-0.001
	(-5.56)	(-5.95)	(-3.79)	(-2.83)	(-2.48)	(-2.96)	(-1.61)	(-0.04)
Observations	1470447	1372799	1378659	673775	145198	135942	137137	53322
Intensive changes	767281	763373	763470	0	89105	88811	88868	0
Entrants	82765	80520	0	70170	7381	7163	0	6413
Exiters	88460	0	86243	76023	8543	0	8329	7490
Stay Unlevered	531941	528906	528946	527582	40169	39968	39940	39419
Number of firms	303695	294443	294629	170378	24610	23963	23996	11655
Within Adj. R^2	0.026	0.030	0.019	0.003	0.018	0.020	0.015	0.002
Dep. var. avg;p50 (in %)	0.8;0	1.3;0	0.2;0	0.4;0	1.2;0	1.6;0	0.9;0	0.2;0
Firm $\mathrm{Controls}_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Macro $\mathrm{Controls}_{\mathrm{c,t\text{-}1}}$	no	no	no	no	no	no	no	no
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Year FE	yes	yes	yes	yes	yes	yes	yes	yes

Table C.4. (*continued*)

Firm Samples:	All				All (pool)			
Margin Changes:	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}	Extensive {entry,exit}	Intensive + Extensive {entry,exit}	Intensive + Extensive {entry}	Intensive + Extensive {exit}	Extensive {entry,exit}
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t\text{-}2}$	-0.297*** (-6.16)	-0.267*** (-6.76)	-0.164*** (-3.98)		-0.281*** (-5.92)	-0.252*** (-6.48)	-0.145*** (-3.55)	
Observations	1616184	1509328	1516374		1640803	1532810	1539878	
Intensive changes	856683	852539	852678		872554	868462	868541	
Entrants	90182	87726	0		91286	88854	0	
Exiters	97036	0	94613		98268	0	95861	
Stay Unlevered	572283	569063	569083		578695	575494	575476	
Number of firms	328372	318478	318694		330706	320905	321018	
Within Adj. R^2	0.010	0.017	0.006		0.010	0.016	0.006	
Dep. var. avg;p50 (in %)	-1.2;0	11.3;0	-12.9;0		-1.2;0	11.3;0	-12.9;0	
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t\text{-}2}$	-0.034*** (-5.83)	-0.036*** (-6.31)	-0.023*** (-4.04)	-0.012** (-2.56)	-0.029*** (-4.81)	-0.031*** (-5.19)	-0.017*** (-2.87)	-0.013*** (-2.66)
Observations	1616184	1509328	1516374	728175	1640803	1532810	1539878	736978
Intensive changes	856683	852539	852678	0	872554	868462	868541	0
Entrants	90182	87726	0	76761	91286	88854	0	77835
Exiters	97036	0	94613	83690	98268	0	95861	84945
Stay Unlevered	572283	569063	569083	567724	578695	575494	575476	574198
Number of firms	328372	318478	318694	182204	330706	320905	321018	183549
Within Adj. R^2	0.025	0.028	0.018	0.003	0.025	0.028	0.018	0.003
Dep. var. avg;p50 (in %)	0.9;0	1.3;0	0.3;0	0.4;0	0.9;0	1.3;0	0.3;0	0.4;0
Firm $\mathrm{Controls}_{i,t\text{-}1}$	yes	yes	yes	yes	yes	yes	yes	yes
Macro $\mathrm{Controls}_{c,t\text{-}1}$	no	no	no	no	no	no	no	no
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Year FE	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi = \alpha + \beta\left(D^{TFP}_{i,t-1} \times CF_{c,MA,t,t-2}\right) + \gamma D^{TFP}_{i,t-1} + \theta_l X^l_{i,t-1} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t}$. The dependent variable Ψ is defined in Panel A as the DHS mid-point growth rate in the outstanding financial (interest bearing) debt y of firm i in year t, while in Panel B, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The table shows results based on an alternative sample (sample C) in which the dependent variable Ψ is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0, thus it includes firms in years they stay unlevered. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and, except for columns 13-16, at the size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.5. Zero Leverage Firms and Capital Inflows, Access to Credit to SMEs

Dependent variable: ***Pr(Z=1)***	**Zero Leverage firms** (Financial Debt ratio=0)				**Almost-Zero Leverage firms** (Financial Debt ratio≤2%)			
Sample:	Including time-invariant firms		Switchers only		Including time-invariant firms		Switchers only	
Min. # obs. per firm:	n.a.	4 years	n.a.	4 years	n.a.	4 years	n.a.	4 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-0.035	-0.046*	-0.167**	-0.179**	-0.033	-0.048**	-0.197***	-0.225***
	(-1.38)	(-1.77)	(-2.11)	(-2.20)	(-1.40)	(-2.05)	(-2.60)	(-3.02)
$D^{TFP}_{i,t-1}$	0.009***	0.011***	0.025***	0.033***	0.006***	0.006***	0.021***	0.022***
	(4.00)	(4.50)	(3.28)	(3.95)	(3.05)	(2.90)	(2.99)	(2.88)
$\text{TFP}_{\text{i,t-1}}$	0.002	0.001	0.006	0.006	0.002	0.002	0.010*	0.011**
	(0.98)	(0.30)	(1.16)	(0.93)	(1.47)	(1.32)	(1.89)	(1.97)
$\text{Collateral}_{\text{i,t-1}}$	0.029***	0.024***	0.065***	0.063***	0.019***	0.017***	0.042***	0.047***
	(5.45)	(4.12)	(4.07)	(3.50)	(3.99)	(3.26)	(2.92)	(2.94)
Ext. Financial $\text{Need}_{\text{i,t-1}}$	0.003*	0.001	0.005	-0.009	0.003**	0.001	0.002	-0.009
	(1.81)	(0.34)	(0.76)	(-1.15)	(2.31)	(0.45)	(0.26)	(-1.13)
Firm $\text{Size}_{\text{i,t-1}}$	0.020***	0.009***	0.059***	0.025***	0.013***	0.002*	0.036***	0.005
	(14.20)	(5.92)	(12.89)	(5.34)	(10.56)	(1.92)	(9.19)	(1.29)
Growth $\text{opp.}_{\text{i,t-1}}$	0.107***	0.123***	0.280***	0.324***	0.094***	0.107***	0.296***	0.309***
	(3.39)	(3.73)	(3.08)	(3.31)	(3.43)	(3.68)	(3.42)	(3.32)
$\text{Profitability}_{\text{i,t-1}}$	-0.003	-0.002*	-0.033***	-0.047**	-0.002	-0.001	-0.052***	-0.053***
	(-1.47)	(-1.69)	(-2.86)	(-2.52)	(-1.37)	(-1.38)	(-3.02)	(-2.80)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	577126	377362	174470	111629	661398	445151	189713	126039
Entrants	58491	25520	52999	25256	62740	28824	56790	28528
Stay Unlevered	518635	351842	121471	86373	598658	416327	132923	97511
Number of firms	149463	66281	45840	20082	166574	76644	48365	22285
# Switchers to $>thrs$%	48483	20175	45840	20082	51214	22383	48365	22285
# Always $\leqslant thrs$%	100980	46106	0	0	115360	54261	0	0
Ption. obs. outside [0;1]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Avg. # years per firm	4.98	6.29	4.83	6.11	5.16	6.45	5.01	6.24
R^2	0.394	0.261	0.188	0.157	0.395	0.265	0.183	0.153
Within Adj. R^2	0.001	0.000	0.002	0.001	0.000	0.000	0.001	0.000
Avg. predicted probability	[0.1014]	[0.0676]	[0.3038]	[0.2263]	[0.0949]	[0.0648]	[0.2994]	[0.2263]

Note: This table reports the results of estimating $Pr(Z{=}1){=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}\big){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where $Z{=}1$ if Financial Debt $\text{ratio}_{t-1}{\leq}thrs$ and Financial Debt $\text{ratio}_t{>}thrs$, otherwise $Z{=}0$ if Financial Debt ratio$\leq thrs$ in $t{-}1$ and t. The left hand side of the table define zero leverage firms with $thrs{=}0$ while the right hand side uses $thrs{=}2$. Regressions focus on the SMEs subsample. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in $t{-}1$ and $t{-}2$, where the cut-off is defined using the median log-TFP at the country-industry-year level and, except for columns (7-8), at the size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t{-}2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

C.2 Complementary Evidence to Section 5

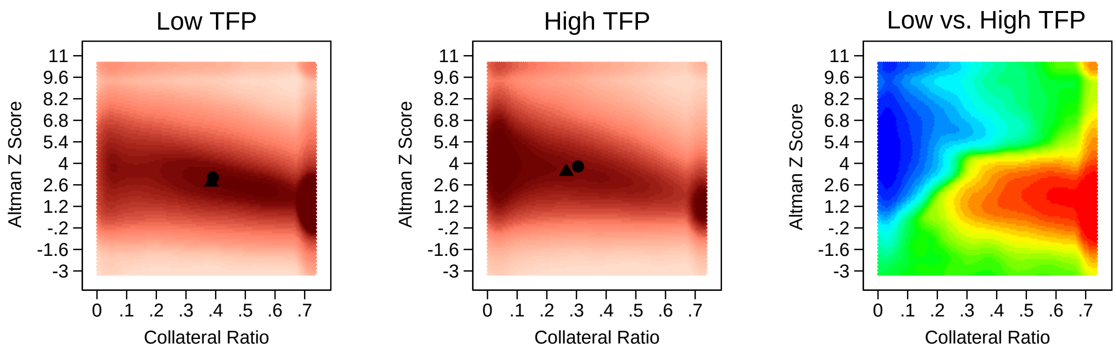
Table C.6. Summary Statistics, Low vs. High TFP Firms (intensive margin sample)

	Low TFP firms				High TFP firms				$\overline{\text{Low}}$ - $\overline{\text{High}}$
	Avg.	Std.	p25;[p50];p75	N	Avg.	Std.	p25;[p50];p75	N	(t-stat)
Panel A: p50									
TFP	1.66	0.74	1.20;[1.60];2.13	383349	2.64	0.82	2.05;[2.51];3.11	442868	-0.98*** (-571)
Labor Productivity	0.93	0.63	0.50;[0.79];1.18	376434	1.60	0.94	0.94;[1.38];2.02	435723	-0.67*** (-371)
Firm Size	6.54	1.63	5.33;[6.30];7.49	383349	7.25	1.59	6.13;[7.18];8.26	442868	-0.71*** (-200)
Collateral Ratio	0.40	0.26	0.18;[0.39];0.60	383349	0.31	0.24	0.10;[0.27];0.48	442868	0.09*** (166)
Cash Ratio	0.08	0.13	0.01;[0.03];0.09	367580	0.09	0.13	0.01;[0.04];0.11	431447	-0.01*** (-36.9)
Altman Z Score	3.25	4.92	1.35;[2.77];4.47	383119	3.98	4.33	1.87;[3.46];5.37	442611	-0.72*** (-71.2)
Debt Overhang Ratio	0.14	0.37	0.02;[0.07];0.17	383335	0.28	0.59	0.06;[0.14];0.30	442862	-0.14*** (-126)
Fin. Leverage Ratio	0.24	0.19	0.09;[0.20];0.35	383349	0.22	0.18	0.08;[0.18];0.32	442868	0.02*** (42.9)
Total Leverage Ratio	0.60	0.24	0.42;[0.62];0.80	383349	0.61	0.23	0.44;[0.63];0.79	442868	0*** (-6.89)
Cash-flow Ratio	0.08	0.10	0.03;[0.07];0.12	371737	0.14	0.12	0.05;[0.11];0.19	437394	-0.05*** (-206)
Profitability Ratio	0.03	0.09	0;[0.02];0.06	383349	0.08	0.11	0.02;[0.05];0.12	442868	-0.05*** (-219)
Panel B: p33-p66									
TFP	1.50	0.73	1.06;[1.44];1.97	229028	2.76	0.82	2.17;[2.61];3.22	335634	-1.26*** (-592)
Labor Productivity	0.85	0.58	0.45;[0.73];1.10	224763	1.70	0.96	1.03;[1.49];2.14	330126	-0.85*** (-377)
Firm Size	6.47	1.65	5.25;[6.20];7.40	229028	7.34	1.58	6.23;[7.28];8.33	335634	-0.86*** (-199)
Collateral Ratio	0.42	0.26	0.20;[0.41];0.63	229028	0.30	0.24	0.09;[0.25];0.47	335634	0.12*** (181)
Cash Ratio	0.08	0.12	0.01;[0.03];0.09	218983	0.09	0.13	0.01;[0.04];0.11	327288	-0.02*** (-43.8)
Altman Z Score	3.12	4.69	1.20;[2.60];4.30	228881	4.04	4.39	1.88;[3.50];5.46	335436	-0.92*** (-74.9)
Debt Overhang Ratio	0.12	0.35	0.01;[0.06];0.15	229016	0.29	0.62	0.06;[0.14];0.31	335630	-0.18*** (-123)
Fin. Leverage Ratio	0.24	0.19	0.09;[0.20];0.35	229028	0.22	0.18	0.08;[0.18];0.32	335634	0.02*** (44.9)
Total Leverage Ratio	0.60	0.24	0.42;[0.62];0.80	229028	0.61	0.23	0.44;[0.63];0.79	335634	-0.01*** (-8.28)
Cash-flow Ratio	0.07	0.09	0.03;[0.06];0.11	220456	0.14	0.13	0.05;[0.11];0.19	331547	-0.07*** (-213)
Profitability Ratio	0.02	0.09	0;[0.01];0.05	229028	0.09	0.12	0.02;[0.05];0.13	335634	-0.06*** (-222)
Panel C: p25-p75									
TFP	1.40	0.73	0.97;[1.34];1.88	159949	2.88	0.83	2.30;[2.73];3.35	241813	-1.49*** (-585)
Labor Productivity	0.81	0.56	0.42;[0.69];1.05	156863	1.82	0.98	1.13;[1.61];2.28	237713	-1.01*** (-370)
Firm Size	6.45	1.67	5.22;[6.17];7.37	159949	7.42	1.57	6.33;[7.39];8.41	241813	-0.97*** (-187)
Collateral Ratio	0.44	0.26	0.22;[0.43];0.65	159949	0.29	0.24	0.08;[0.24];0.46	241813	0.15*** (180)
Cash Ratio	0.07	0.12	0.01;[0.03];0.08	152649	0.09	0.13	0.01;[0.04];0.12	236061	-0.02*** (-45.6)
Altman Z Score	3.07	5.00	1.12;[2.51];4.20	159832	4.10	4.68	1.89;[3.54];5.53	241649	-1.03*** (-66.3)
Debt Overhang Ratio	0.10	0.35	0.01;[0.06];0.14	159939	0.31	0.65	0.06;[0.14];0.32	241809	-0.20*** (-115)
Fin. Leverage Ratio	0.24	0.19	0.09;[0.20];0.36	159949	0.22	0.18	0.07;[0.18];0.32	241813	0.03*** (42.7)
Total Leverage Ratio	0.60	0.24	0.41;[0.62];0.80	159949	0.61	0.23	0.44;[0.63];0.79	241813	-0.01*** (-12.4)
Cash-flow Ratio	0.06	0.09	0.02;[0.05];0.10	153073	0.14	0.13	0.06;[0.11];0.20	238875	-0.08*** (-205)
Profitability Ratio	0.02	0.09	0;[0.01];0.04	159949	0.09	0.12	0.02;[0.06];0.13	241813	-0.07*** (-211)

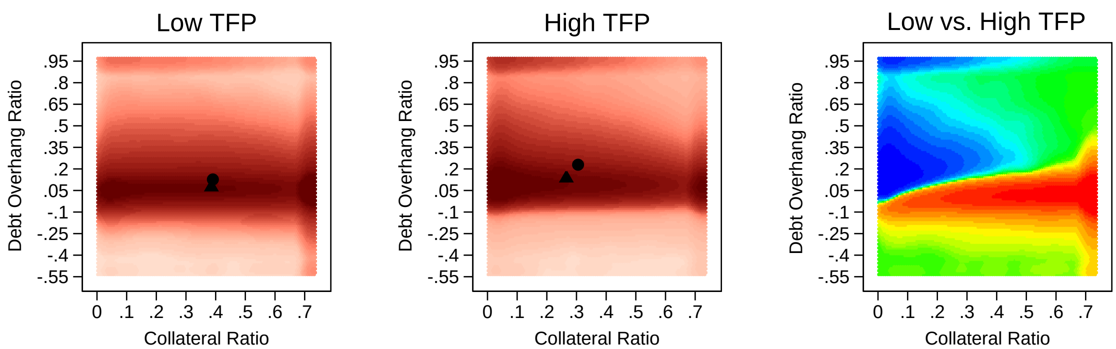
Note: This table presents summary statistics on low TFP versus high TFP firms and is based on the estimation sample that focuses on the intensive margin of credit growth (Sample A). Low and high TFP firms are defined according to our D^{TFP} dummy that is equal to 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median (p50) log-TFP in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-year and size class (SME, large) level. ***p<0.01, **p<0.05, *p<0.1.

Figure C.I. Density Plots, Low vs. High TFP Firms (intensive margin sample)

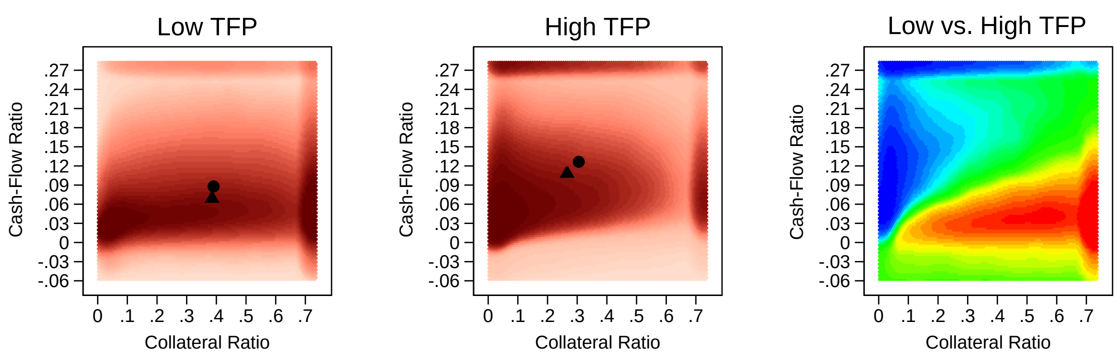
(a) Risk: Altman's Z Score

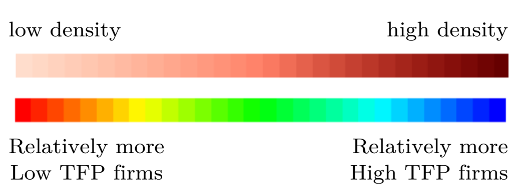


(b) Risk: Debt Overhang Ratio



(c) Risk: Cash-Flow Ratio





Note: This figure plots empirical bivariate densities of low TFP versus high TFP firms as a function of firm's collateral and several risk proxies. It is based on the estimation sample that focuses on the intensive margin of credit growth (Sample A). Figures on the right-hand side present relative density distribution plots. Low and high TFP firms are defined according to our D^{TFP} dummy that equals 1 if a firm is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level.

Table C.7. Debt Growth and Capital Inflows, Other Firm Characteristics (Intensive and Extensive Margin Changes)

Margin Changes & Dependent variable	**Intensive + Extensive** $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$						**Intensive + Extensive** $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$					
Firm-level Proxies:	Altman's Z Score	Debt Overhang	Cash-Flow Ratio	Leverage Ratio	Collateral Ratio	Cash Ratio	Altman's Z Score	Debt Overhang	Cash-Flow Ratio	Leverage Ratio	Collateral Ratio	Cash Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: p50												
$D^{Proxy}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$	-0.605***	-0.347***	-0.360***	0.214***	0.176***	-0.102	-0.165***	-0.135***	-0.105***	0.164***	0.084***	-0.116***
	(-9.12)	(-5.58)	(-5.01)	(3.34)	(2.84)	(-1.37)	(-19.63)	(-15.48)	(-10.31)	(18.57)	(11.59)	(-14.91)
Observations	996977	1038291	912997	1063183	1073118	917353	996977	1038291	912997	1063183	1073118	917353
% Extensive changes	16.3%	16.5%	16.2%	16.4%	16.4%	16.3%	16.3%	16.5%	16.2%	16.4%	16.4%	16.3%
Number of firms	220002	225509	209562	226935	226595	209984	220002	225509	209562	226935	226595	209984
Within Adj. R^2	0.017	0.017	0.016	0.018	0.016	0.017	0.048	0.049	0.047	0.053	0.045	0.047
Panel B: p33-p66												
$D^{Proxy}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$	-0.926***	-0.693***	-0.459***	0.484***	0.326***	-0.077	-0.229***	-0.194***	-0.143***	0.246***	0.121***	-0.163***
	(-10.28)	(-7.63)	(-4.71)	(5.26)	(3.82)	(-0.77)	(-22.47)	(-18.13)	(-11.13)	(22.23)	(12.04)	(-16.00)
Observations	647518	666628	612477	713961	735799	613511	647518	666628	612477	713961	735799	613511
% Extensive changes	17.6%	18.2%	16.8%	16.6%	15.9%	16.2%	17.6%	18.2%	16.8%	16.6%	15.9%	16.2%
Number of firms	164130	168861	161275	172940	171380	160375	164130	168861	161275	172940	171380	160375
Within Adj. R^2	0.017	0.017	0.018	0.016	0.016	0.018	0.049	0.047	0.049	0.048	0.047	0.048
Panel C: p25-p75												
$D^{Proxy}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$	-1.211***	-0.886***	-0.437***	0.759***	0.382***	0.007	-0.273***	-0.232***	-0.180***	0.303***	0.128***	-0.196***
	(-9.58)	(-7.22)	(-3.64)	(6.05)	(3.38)	(0.05)	(-20.76)	(-17.69)	(-11.08)	(21.29)	(10.37)	(-14.84)
Observations	439317	451948	419267	502256	534757	427099	439317	451948	419267	502256	534757	427099
% Extensive changes	18.6%	19.6%	17.4%	16.9%	15.5%	15.9%	18.6%	19.6%	17.4%	16.9%	15.5%	15.9%
Number of firms	120643	125426	121056	130239	131123	120786	120643	125426	121056	130239	131123	120786
Within Adj. R^2	0.017	0.016	0.019	0.014	0.015	0.018	0.048	0.046	0.050	0.045	0.047	0.048
Firm $\mathrm{Controls}_{i,t-1}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Macro $\mathrm{Controls}_{c,t-1}$	no	no	no	no	no	no	no	no	no	no	no	no
Baseline Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi=\alpha+\beta\left(D^{Proxy}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma D^{Proxy}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. The dependent variable Ψ is defined in columns 1-6 as the DHS mid-point growth rate in the outstanding financial debt y of firm i in year t, while in columns 7-12, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{Proxy} is a time-varying dummy that equals 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median (p50) in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-size-year level. *Proxy* is defined in the table, and each measure is further descibed in Table 4. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, and growth opportunities. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.8. Debt Growth and Capital Inflows, Other Firm Characteristics (Including Years a Firm Stays Unlevered)

Margin Changes & Dependent variable	**Intensive + Extensive** $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$						**Intensive + Extensive** $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$					
Firm-level Proxies:	Altman's Z Score	Debt Overhang	Cash-Flow Ratio	Leverage Ratio	Collateral Ratio	Cash Ratio	Altman's Z Score	Debt Overhang	Cash-Flow Ratio	Leverage Ratio	Collateral Ratio	Cash Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: p50												
$D^{Proxy}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.833***	-0.612***	-0.430***	0.637***	0.525***	-0.689***	-0.136***	-0.113***	-0.080***	0.146***	0.087***	-0.124***
	(-17.80)	(-13.40)	(-8.11)	(13.51)	(12.56)	(-14.32)	(-22.68)	(-18.64)	(-11.72)	(21.86)	(16.41)	(-22.48)
Observations	1576298	1639300	1432733	1674280	1691378	1471008	1576298	1639300	1432733	1674280	1691378	1471008
% Extensive changes	11.4%	11.6%	11.5%	11.4%	11.5%	11.3%	11.4%	11.6%	11.5%	11.4%	11.5%	11.3%
% Stay Unlevered	35.4%	35.4%	34.7%	35.2%	35.3%	36.1%	35.4%	35.4%	34.7%	35.2%	35.3%	36.1%
Number of firms	324895	331842	309980	333460	333646	313620	324895	331842	309980	333460	333646	313620
Panel B: p33-p66												
$D^{Proxy}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-1.091***	-0.890***	-0.589***	0.954***	0.816***	-0.955***	-0.166***	-0.138***	-0.103***	0.186***	0.122***	-0.169***
	(-18.67)	(-14.58)	(-8.55)	(15.50)	(14.92)	(-16.09)	(-23.84)	(-19.89)	(-12.33)	(23.19)	(16.37)	(-24.41)
Observations	1096788	1135731	993826	1170089	1170473	1021362	1096788	1135731	993826	1170089	1170473	1021362
% Extensive changes	11.8%	12.1%	11.9%	11.5%	11.3%	11.2%	11.8%	12.1%	11.9%	11.5%	11.3%	11.2%
% Stay Unlevered	39.1%	39.6%	36.3%	37.3%	35.5%	38.0%	39.1%	39.6%	36.3%	37.3%	35.5%	38.0%
Number of firms	254933	261700	245942	264396	259713	246214	254933	261700	245942	264396	259713	246214
Panel C: p25-p75												
$D^{Proxy}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-1.290***	-1.014***	-0.642***	1.225***	0.942***	-1.105***	-0.183***	-0.144***	-0.126***	0.217***	0.131***	-0.199***
	(-17.43)	(-13.66)	(-7.97)	(15.92)	(13.89)	(-14.90)	(-21.42)	(-18.10)	(-12.68)	(21.91)	(14.66)	(-23.16)
Observations	793135	826387	702622	856620	859794	729504	793135	826387	702622	856620	859794	729504
% Extensive changes	12.0%	12.4%	12.2%	11.5%	11.1%	10.9%	12.0%	12.4%	12.2%	11.5%	11.1%	10.9%
% Stay Unlevered	42.5%	43.3%	37.9%	39.4%	36.0%	39.3%	42.5%	43.3%	37.9%	39.4%	36.0%	39.3%
Number of firms	197469	205220	190312	207254	202786	189366	197469	205220	190312	207254	202786	189366
Firm Controls$_{i,t-1}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Macro Controls$_{c,t-1}$	no	no	no	no	no	no	no	no	no	no	no	no
Baseline Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\big(D^{Proxy}_{i,t-1}{\times}CF_{c,MA,t,t-2}\big){+}\gamma D^{Proxy}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$. The dependent variable Ψ is defined in columns 1-6 as the DHS mid-point growth rate in the outstanding financial debt y of firm i in year t, while in columns 7-12, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. Ψ is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0 (sample C). One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{Proxy} is a time-varying dummy that equals 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median (p50) in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-size-year level. *Proxy* is defined in the table, and each measure is further descibed in Table 4. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t and $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, and growth opportunities. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.9. Debt Growth and Capital Inflows, TFP–Financial Constraints and TFP–Risk (All Proxies)

Margin Changes: **Intensive only**
Dependent variable: $\Delta \ln\left(y_{i,t}\right)$

	Dimension 1: TFP (H•: High TFP, p50 cutoff); Dimension 2:														
	Collateral Ratio (•H : High Collateral)			**Cash Ratio** (•H : Low Cash)			**Altman's Z Score** (•H : High Risk)			**Debt Overhang Ratio** (•H : High Risk)			**Cash-Flow Ratio** (•H : High Risk)		
Cut-off for Dimension 2	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$CF_{c,MAt,t-2}$ [HH-LH]	-0.15** (-2.50)	-0.05 (-0.75)	0.05 (0.62)	-0.12* (-1.77)	-0.09 (-1.11)	-0.16* (-1.67)	-0.05 (-0.77)	0.06 (0.71)	0.06 (0.52)	-0.10* (-1.66)	0.03 (0.32)	0.13 (1.09)	-0.10 (-1.62)	-0.08 (-0.87)	0.00 (0.03)
$CF_{c,MAt,t-2}$ [LL-LH]	-0.17** (-2.33)	-0.15 (-1.40)	-0.05 (-0.37)	-0.17** (-2.17)	-0.15 (-1.42)	-0.42*** (-2.84)	-0.39*** (-4.89)	-0.61*** (-5.30)	-0.90*** (-5.47)	-0.23*** (-2.78)	-0.39*** (-3.32)	-0.60*** (-3.39)	-0.13 (-1.61)	-0.24** (-2.16)	-0.31* (-1.95)
$CF_{c,MAt,t-2}$ [HL-LH]	-0.52*** (-7.59)	-0.56*** (-6.48)	-0.46*** (-4.22)	-0.58*** (-7.45)	-0.73*** (-7.22)	-0.82*** (-6.18)	-0.76*** (-10.35)	-1.04*** (-10.32)	-1.35*** (-9.71)	-0.58*** (-8.10)	-0.80*** (-8.08)	-0.98*** (-7.37)	-0.50*** (-6.48)	-0.63*** (-6.47)	-0.75*** (-6.08)
$CF_{c,MAt,t-2}$ [HH-LL]	0.02 (0.28)	0.10 (0.87)	0.10 (0.71)	0.05 (0.61)	0.06 (0.57)	0.26* (1.75)	0.34*** (4.12)	0.67*** (5.59)	0.96*** (5.62)	0.12 (1.52)	0.42*** (3.45)	0.73*** (4.08)	0.03 (0.30)	0.17 (1.38)	0.32* (1.83)
$CF_{c,MAt,t-2}$ [HH-HL]	0.37*** (5.68)	0.50*** (5.70)	0.51*** (4.50)	0.46*** (6.13)	0.64*** (6.51)	0.65*** (5.20)	0.72*** ((10.05)	1.10*** ((11.35)	1.40*** ((10.24)	0.48*** (7.14)	0.83*** (8.29)	1.11*** (8.09)	0.39*** (5.39)	0.56*** (5.23)	0.76*** (5.68)
$CF_{c,MAt,t-2}$ [LL-HL]	0.35*** (4.09)	0.41*** (3.38)	0.42*** (2.59)	0.41*** (4.56)	0.58*** (4.65)	0.39** (2.33)	0.37*** (4.02)	0.43*** (3.39)	0.44** (2.41)	0.35*** (4.05)	0.40*** (3.21)	0.38** (2.05)	0.37*** (4.20)	0.39*** (3.36)	0.44*** (2.77)
Test H0: •H=•L (p-value)	18.45*** (0.000)	16.94*** (0.000)	10.22*** (0.000)	20.39*** (0.000)	22.25*** (0.000)	17.02*** (0.000)	61.890*** (0.000)	74.520*** (0.000)	63.390*** (0.000)	28.95*** (0.000)	38.61*** (0.000)	37.25*** (0.000)	15.02*** (0.000)	14.85*** (0.000)	16.72*** (0.000)
Test H0: H•=L• (p-value)	10.31*** (0.000)	5.90*** (0.000)	3.57** (0.030)	11.11*** (0.000)	11.27*** (0.000)	3.97** (0.020)	8.17*** (0.000)	6.27*** (0.000)	3.13** (0.040)	9.26*** (0.000)	5.24*** (0.010)	2.66* (0.070)	9.44*** (0.000)	6.02*** (0.000)	3.86** (0.020)
Observations	743527	505024	366154	633862	413276	284091	694094	431904	284584	718240	440028	287259	640087	414645	276233
Number of firms	173929	127876	96703	158828	116150	85203	168472	118505	83487	172534	121754	86068	160168	117547	84705
Within R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Relative Ranking$^{[\%obs.]}$	$LH^{[32\%]}$ $HH^{[27\%]}$ $LL^{[15\%]}$ $HL^{[26\%]}$	$LH^{[37\%]}$ $HH^{[29\%]}$ $LL^{[11\%]}$ $HL^{[23\%]}$	$HH^{[28\%]}$ $LH^{[39\%]}$ $LL^{[10\%]}$ $HL^{[23\%]}$	$LH^{[31\%]}$ $HH^{[34\%]}$ $LL^{[15\%]}$ $HL^{[20\%]}$	$LH^{[31\%]}$ $HH^{[32\%]}$ $LL^{[15\%]}$ $HL^{[21\%]}$	$LH^{[33\%]}$ $HH^{[34\%]}$ $LL^{[14\%]}$ $HL^{[20\%]}$	$LH^{[32\%]}$ $HH^{[29\%]}$ $LL^{[15\%]}$ $HL^{[24\%]}$	$HH^{[27\%]}$ $LH^{[33\%]}$ $LL^{[15\%]}$ $HL^{[26\%]}$	$HH^{[28\%]}$ $LH^{[36\%]}$ $LL^{[13\%]}$ $HL^{[24\%]}$	$LH^{[33\%]}$ $HH^{[26\%]}$ $LL^{[14\%]}$ $HL^{[27\%]}$	$HH^{[23\%]}$ $LH^{[35\%]}$ $LL^{[13\%]}$ $HL^{[29\%]}$	$HH^{[21\%]}$ $LH^{[39\%]}$ $LL^{[11\%]}$ $HL^{[28\%]}$	$LH^{[32\%]}$ $HH^{[24\%]}$ $LL^{[14\%]}$ $HL^{[30\%]}$	$LH^{[31\%]}$ $HH^{[20\%]}$ $LL^{[14\%]}$ $HL^{[35\%]}$	$HH^{[19\%]}$ $LH^{[32\%]}$ $LL^{[13\%]}$ $HL^{[36\%]}$

Note: This table reports the results of estimating $\Delta \ln(y_{i,t}) = \alpha + \beta\left(D^{TFP}_{i,t-1} \times D^{Proxy}_{i,t-1} \times CF_{c,MA,t,t-2}\right) + \gamma_1 D^{TFP}_{i,t-1} + \gamma_2 D^{Proxy}_{i,t-1} + \delta_1\left(D^{TFP}_{i,t-1} \times CF_{c,MA,t,t-2}\right) + \delta_2\left(D^{Proxy}_{i,t-1} \times CF_{c,MA,t,t-2}\right) + \theta_l X^l_{i,t-1} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t}$. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The dependent variable is the log-difference of outstanding financial debt of firm i in year t, thus focusing on debt changes at the intensive margin only. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year-size class (SME, large) level. Similarly defined, the dummy D^{Proxy} uses as cut-offs either the median, the p33-p66, or the p25-p75 thresholds. *Proxy*, i.e. dimension 2, is defined in the table. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities, and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.10. Debt Growth and Capital Inflows, TFP–Collateral and TFP–Risk, Intensive and Extensive Margins Changes

Margin Changes & Dependent variable	**Intensive + Extensive** $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$						**Intensive + Extensive** $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$					
	Dimension 1: TFP (H•: High TFP, p50 cutoff); **Dimension 2:**						**Dimension 1: TFP** (H•: High TFP, p50 cutoff); **Dimension 2:**					
	Collateral Ratio (•H : High Collateral)			**Altman's Z Score** (•H : High Risk)			**Collateral Ratio** (•H : High Collateral)			**Altman's Z Score** (•H : High Risk)		
Cut-off for Dimension 2	p50 (1)	p33-p66 (2)	p25-p75 (3)	p50 (4)	p33-p66 (5)	p25-p75 (6)	p50 (7)	p33-p66 (8)	p25-p75 (9)	p50 (10)	p33-p66 (11)	p25-p75 (12)
$CF_{c,MAt,t-2}$ [HH-LH]	-0.39***	-0.30***	-0.23**	-0.15*	-0.12	-0.21	-0.03***	-0.01	0.01	-0.01	0.02	0.02
	(-5.01)	(-3.30)	(-2.14)	(-1.87)	(-1.02)	(-1.47)	(-2.73)	(-0.99)	(0.69)	(-1.03)	(1.35)	(1.01)
$CF_{c,MAt,t-2}$ [LL-LH]	-0.03	-0.03	-0.07	-0.37***	-0.53***	-0.80***	-0.05***	-0.07***	-0.06***	-0.13***	-0.16***	-0.22***
	(-0.31)	(-0.19)	(-0.37)	(-3.51)	(-3.49)	(-3.75)	(-4.38)	(-4.17)	(-2.88)	(-10.12)	(-10.13)	(-10.63)
$CF_{c,MAt,t-2}$ [HL-LH]	-0.54***	-0.63***	-0.65***	-0.96***	-1.28***	-1.62***	-0.13***	-0.16***	-0.16***	-0.21***	-0.26***	-0.31***
	(-6.11)	(-5.39)	(-4.36)	(-10.20)	(-10.21)	(-9.31)	(-12.51)	(-11.93)	(-9.74)	(-16.91)	(-17.56)	(-16.78)
$CF_{c,MAt,t-2}$ [HH-LL]	-0.36***	-0.27*	-0.16	0.22**	0.41***	0.59***	0.02	0.06***	0.07***	0.12***	0.18***	0.23***
	(-3.18)	(-1.72)	(-0.79)	(1.97)	(2.64)	(2.71)	(1.54)	(3.04)	(3.08)	(8.37)	(11.01)	(11.00)
$CF_{c,MAt,t-2}$ [HH-HL]	0.15*	0.33***	0.42***	0.80***	1.17***	1.41***	0.10***	0.14***	0.17***	0.20***	0.28***	0.32***
	(1.82)	(2.93)	(2.87)	(8.95)	(9.35)	(8.16)	((10.07)	((10.68)	(9.39)	((17.02)	((19.70)	((17.80)
$CF_{c,MAt,t-2}$ [LL-HL]	0.51***	0.60***	0.58***	0.59***	0.76***	0.82***	0.08***	0.09***	0.10***	0.08***	0.10***	0.09***
	(4.41)	(3.60)	(2.67)	(5.01)	(4.65)	(3.57)	(6.35)	(4.85)	(4.33)	(5.53)	(6.09)	(4.45)
Test H0: •H=•L	1.67	4.30***	4.13**	45.19***	49.56***	38.58***	55.640***	60.310***	46.05***	181.850***	237.990***	195.620***
(p-value)	(0.190)	(0.010)	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Test H0: H•=L•	19.39***	10.75***	5.56***	13.53***	11.14***	7.28***	20.90***	11.79***	9.78***	15.31***	20.17***	10.71***
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	919728	623184	450917	858486	548335	368778	919728	623184	450917	858486	548335	368778
% Extensive changes	16.3%	15.8%	15.4%	16.2%	17.4%	18.3%	16.3%	15.8%	15.4%	16.2%	17.4%	18.3%
Number of firms	211564	156372	118323	205103	148239	106878	211564	156372	118323	205103	148239	106878
Relative Ranking[%obs.]	$LH^{[31\%]}$ LL[15%] HH[26%] HL[28%]	$LH^{[36\%]}$ LL[12%] HH[27%] HL[25%]	$LH^{[38\%]}$ LL[11%] HH[26%] HL[25%]	$LH^{[30\%]}$ HH[28%] LL[17%] HL[25%]	$LH^{[30\%]}$ HH[25%] LL[17%] HL[28%]	$LH^{[32\%]}$ HH[26%] LL[15%] HL[27%]	$LH^{[31\%]}$ HH[26%] LL[15%] HL[28%]	$LH^{[36\%]}$ HH[27%] LL[12%] HL[25%]	HH[26%] $LH^{[38\%]}$ LL[11%] HL[25%]	$LH^{[30\%]}$ HH[28%] LL[17%] HL[25%]	HH[25%] $LH^{[30\%]}$ LL[17%] HL[28%]	HH[26%] $LH^{[32\%]}$ LL[15%] HL[27%]

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\left(D^{TFP}_{i,t-1}\times D^{Proxy}_{i,t-1}\times CF_{c,MA,t,t-2}\right){+}\gamma_1 D^{TFP}_{i,t-1}{+}\gamma_2 D^{Proxy}_{i,t-1}{+}\delta_1\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right){+}\delta_2\left(D^{Proxy}_{i,t-1}\times CF_{c,MA,t,t-2}\right){+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$. The dependent variable Ψ is defined in columns 1-6 as the DHS mid-point growth rate in the outstanding financial debt y of firm i in year t, while in columns 7-12, Ψ is computed as the firm's change in financial debt from the previous period scaled by lagged total assets. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year-size class (SME, large) level. Similarly defined, the dummy D^{Proxy} uses as cut-offs either the median, the p33-p66, or the p25-p75 thresholds. *Proxy*, i.e. dimension 2, is defined in the table. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities, and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.11. Debt Growth and Capital Inflows, Productivity–Collateral–Risk (Debt Overhang)

Margin Changes: **Intensive only** *Dependent variable*: $\Delta\ln(y_{i,t})$	**Risk proxy: Debt Overhang**														
	TFP			**TFP–Collateral** (•H : High Collateral)			**TFP–Risk** (•H : High Risk)			**TFP–Collateral–Risk** (quadruple interaction=0)			**TFP–Collateral–Risk** (8 categories)		
Cut-off for Collateral and Risk dummies	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75	p50	p33-p66	p25-p75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-0.28***	-0.37***	-0.55***	-0.24***	-0.30***	-0.49***	-0.21***	-0.03	0.08	-0.17***	0.04	0.14			
	(-5.02)	(-3.71)	(-3.31)	(-4.26)	(-2.99)	(-2.89)	(-3.70)	(-0.26)	(0.47)	(-3.04)	(0.39)	(0.78)			
$D^{COL}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$				0.25***	0.33***	0.27				0.23***	0.32***	0.24			
				(4.47)	(2.87)	(1.39)				(4.17)	(2.80)	(1.24)			
$D^{RISK}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$							0.40***	1.17***	1.73***	0.40***	1.18***	1.73***			
							(7.34)	(10.63)	(8.68)	(7.30)	(10.71)	(8.69)			
Test H0: H••=L•• [TFP]													**3.62*****	**0.90**	**1.13**
(p-value)													**(0.010)**	**(0.470)**	**(0.340)**
Test H0: •H•= •L• [COL]													**6.08*****	**3.77*****	**1.65**
(p-value)													**(0.000)**	**(0.000)**	**(0.160)**
Test H0: ••H=••L [RISK]													**16.180*****	**30.610*****	**19.750*****
(p-value)													**(0.000)**	**(0.000)**	**(0.000)**
$\text{CF}_{\text{c,MAt,t-2}}$ [Hrest-LHH]													-0.23***	-0.32***	-0.49***
													(-3.35)	(-2.86)	(-2.70)
$\text{CF}_{\text{c,MAt,t-2}}$ [Hrest - Lrest]													-0.08	0.21	0.22
													(-1.22)	(1.53)	(0.93)
$\text{CF}_{\text{c,MAt,t-2}}$ [Hrest - HLL]													0.54***	1.13***	1.31***
													(6.12)	(5.95)	(4.15)
$\text{CF}_{\text{c,MAt,t-2}}$ [Lrest-LHH]													-0.15**	-0.53***	-0.71***
													(-2.10)	(-3.99)	(-3.25)
$\text{CF}_{\text{c,MAt,t-2}}$ [Lrest - HLL]													0.62***	0.93***	1.09***
													(6.38)	(4.47)	(3.15)
$\text{CF}_{\text{c,MAt,t-2}}$ [HLL-LHH]													-0.77***	-1.46***	-1.80***
													(-7.99)	(-7.58)	(-5.73)
Observations	625351	252806	117746	625351	252806	117746	625351	252806	117746	625351	252806	117746	625351	252806	117746
Number of firms	157156	76413	38659	157156	76413	38659	157156	76413	38659	157156	76413	38659	157156	76413	38659
Within R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Relative Ranking[%obs.]	L[47%] H[53%]	L[51%] H[49%]	L[55%] H[45%]	LH[33%] HH[27%] LL[14%] HL[26%]	LH[39%] HH[27%] LL[12%] HL[22%]	LH[43%] HH[24%] LL[12%] HL[21%]	LH[34%] HH[26%] LL[13%] HL[27%]	LH[39%] HH[22%] LL[12%] HL[27%]	HH[21%] LH[45%] HL[24%] LL[10%]				LHH[24%] Lrest[23%] Hrest[40%] HLL[14%]	LHH[29%] Hrest[37%] Lrest[21%] HLL[13%]	LHH[36%] Hrest[33%] Lrest[19%] HLL[12%]

Note: Details on the respective regressions ran in this table are given in the main text. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high TFP bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. D^{COL} and D^{RISK} are time-varying dummies that equal 1 if a firm i is in the high bin in t-1 and t-2, where the cut-off is defined using the median, terciles or quartiles in the collateral ratio or in the debt overhang ratio at the country-industry-size-year level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities, and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

C.3 Complementary Evidence to Section 6

Table C.12. TFP Ex-post Cumulative Growth and Debt Change, Ex-ante High versus Low TFP Firms

Firm Samples:	All		ex-ante High TFP		ex-ante Low TFP	
Differentiate Debt Chg.	n.a.	$+vs.-$	n.a.	$+vs.-$	n.a.	$+vs.-$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Intensive margin						
Δ $\mathrm{Debt_{i,t}}$ $:=\Delta\ln(y_{i,t})$	0.021***		0.020***		0.021***	
	(22.29)		(15.20)		(15.40)	
⋄ Δ $\mathrm{Debt_{i,t}}^{+}$		0.007***		0.009***		0.003
		(3.62)		(3.62)		(1.19)
⋄ Δ $\mathrm{Debt_{i,t}}^{-}$		0.033***		0.028***		0.037***
		(14.82)		(8.94)		(11.29)
⋄ Δ $\mathrm{Debt_{i,t}}^{+vs.-}$		-0.026***		-0.019***		-0.033***
		(-8.48)		(-4.41)		(-7.21)
Observations	502661	502661	267520	267520	213890	213890
% Extensive changes	0%	0%	0%	0%	0%	0%
Number of firms	118207	118207	64842	64842	56267	56267
Within Adj. R^2	0.055	0.056	0.041	0.041	0.022	0.023
Panel B: Intensive + Extensive margins						
Δ $\mathrm{Debt_{i,t}}$ $:=\frac{\Delta y_{i,t}}{Assets_{i,t-1}}$	0.148***		0.143***		0.156***	
	(26.89)		(18.56)		(18.74)	
⋄ Δ $\mathrm{Debt_{i,t}}^{+}$		0.082***		0.111***		0.044***
		(8.71)		(8.61)		(3.05)
⋄ Δ $\mathrm{Debt_{i,t}}^{-}$		0.264***		0.211***		0.330***
		(15.44)		(8.65)		(13.06)
⋄ Δ $\mathrm{Debt_{i,t}}^{+vs.-}$		-0.183***		-0.100***		-0.286***
		(-8.84)		(-3.44)		(-9.21)
Observations	614887	614887	327746	327746	261304	261304
% Extensive changes	15.6%	15.6%	15.5%	15.5%	15.0%	15.0%
Number of firms	141871	141871	78395	78395	67731	67731
Within Adj. R^2	0.056	0.057	0.041	0.041	0.022	0.023
Firm $\mathrm{Controls_{i,t-1}}$	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $TFP_{i,t+2}-TFP_{i,t}=\psi\Delta Debt_{i,t}+\theta_l X^l_{i,t}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t+2}$, and its variants, wherein the dependent variable is the firms' cumulative TFP growth between t+2 and t. Firm's debt change ($\Delta Debt_{i,t}$) is measured either as the simple log-difference of financial debt positions (panel A) or as the first difference of financial debt scaled by lagged assets to accommodate adjustments on both the intensive and extensive margins (panel B). Columns (2), (4) and (6) augment the specification with an interaction of $\Delta Debt_{i,t}$ with an indicator variable differentiating positive versus negative debt changes. Columns (3-4) and (5-6) further split the sample of firms based on the productivity dummy D^{TFP} that distinguishes high from low TFP firms within the same country-industry-size-year strata. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. Firm controls X dated in year t include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the firm-level. ***p<0.01, **p<0.05, *p<0.1.

Table C.13. Contrasts betwen CEE12 and Adv10 Samples, WLS results, Including Years a Firm Stays Unlevered

Margin Changes	**Intensive + Extensive** including years a firm stays unlevered (sample C)							
Country coverage:	**Emerging Countries (CEE12)**				**Advanced Countries (Adv10)**			
Weighting Schemes:	No	ctry×year	empl	turnover	No	ctry×year	empl	turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **OUT - IN**	0.157	0.363	0.715	0.346	-0.298***	-0.224***	-0.306***	-0.303***
	(0.81)	(1.63)	(1.38)	(1.02)	(-7.63)	(-2.81)	(-4.01)	(-5.85)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **IN**	-0.317***	-0.458***	-0.762***	-0.474***	0.037*	-0.009	0.013	0.009
	(-4.76)	(-6.22)	(-4.09)	(-4.63)	(1.69)	(-0.19)	(0.31)	(0.34)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **OUT**	-0.160	-0.095	-0.046	-0.128	-0.261***	-0.233***	-0.293***	-0.294***
	(-0.86)	(-0.44)	(-0.09)	(-0.38)	(-7.18)	(-3.17)	(-4.09)	(-5.99)
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **OUT - IN**	0.008	0.035	0.025	0.005	-0.026***	-0.039***	-0.039***	-0.032***
	(0.32)	(1.23)	(0.58)	(0.18)	(-4.68)	(-4.04)	(-4.23)	(-4.56)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **IN**	-0.037***	-0.058***	-0.060***	-0.041***	0.001	-0.002	0.003	0.001
	(-4.93)	(-5.72)	(-3.54)	(-3.96)	(0.43)	(-0.35)	(0.66)	(0.37)
⋄ $D^{TFP}_{i,t-1} \times \mathrm{CF}_{c,MAt,t-2}$ **OUT**	-0.030	-0.023	-0.035	-0.035	-0.025***	-0.041***	-0.036***	-0.031***
	(-1.34)	(-0.85)	(-0.83)	(-1.21)	(-4.76)	(-4.55)	(-4.29)	(-4.73)
Firm Controls$_{i,t-1}$	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s\times t$, $c\times t$, $c\times s$	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1616184	1616184	1616184	1616184	8256055	8256055	8256055	8256055
⋄ Intensive changes	856683	856683	856683	856683	5446816	5446816	5446816	5446816
⋄ Extensive changes	187218	187218	187218	187218	929010	929010	929010	929010
⋄ Stay Unlevered	572283	572283	572283	572283	1880229	1880229	1880229	1880229
Number of firms	328372	328372	328372	328372	1430506	1430506	1430506	1430506

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}{\times}D^{OUT}\big){+}\gamma D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-2}{+}\delta_1 D^{TFP}_{i,t-1}{\times}D^{OUT}{+}\delta_2 D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where the dependent variable Ψ is defined in each panel of the table, and is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0, (sample C). $y_{i,t}$ denotes the outstanding financial debt of firm i in year t. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. Except for columns 1 and 5 that are estimated using OLS, the rest of the columns are estimated using WLS, where the re-sampling weights are defined as follows: weigth ‘‘*ctry×year*’’ is equal to the inverse of the number of a country's observations in a given year as a share of all observations in that year (i.e. $w_{c,t}{=}N_t/N_{c,t}$); weigths ‘‘*empl*’’ and ‘‘*turnover*’’ are based on the number of employees or turnover, respectively, in each SDBS country-industry(2digits)-size(4 size classes based on the number of employees) class cell to ‘‘scale up’’ the number of ORBIS observations in each cell so that they match those observed in the OECD's SDBS aggregate data. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and size class (SME, large) level. *CF* is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. D^{OUT} denotes an outflow dummy which equals 1 when capital inflows are negative. We multiplied these negative inflows by -1, so that higher CF^{OUT} implies an increase in capital outflows, i.e., non-residents disinvest to a greater extent. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1

Table C.14. Firm's Debt Growth and Capital Inflows, WLS, CEE12 Country Group, CF at Time t

Margin Changes	Intensive + Extensive							
Sample:	Baseline: (sample B) excluding years a firm stays unlevered				Alternative: (sample C) including years a firm stays unlevered			
Weighting Schemes:	No	ctry×year	empl	turnover	No	ctry×year	empl	turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{OUT\ -\ IN}}$	-0.458***	-0.412**	-0.953*	-0.797**	-0.242**	-0.093	-0.536*	-0.367**
	(-2.77)	(-2.21)	(-1.87)	(-2.52)	(-2.28)	(-0.74)	(-1.73)	(-2.03)
◇ $D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{IN}}$	-0.406***	-0.586***	-1.193***	-0.914***	-0.270***	-0.461***	-0.749***	-0.531***
	(-4.80)	(-6.57)	(-4.78)	(-5.51)	(-5.07)	(-7.46)	(-4.65)	(-5.74)
◇ $D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{OUT}}$	-0.864***	-0.998***	-2.146***	-1.711***	-0.511***	-0.555***	-1.286***	-0.899***
	(-5.77)	(-5.79)	(-4.65)	(-6.07)	(-5.20)	(-4.79)	(-4.64)	(-5.40)
Panel B. Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$								
$D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{OUT\ -\ IN}}$	-0.027	-0.015	-0.076*	-0.074***	-0.015	0.008	-0.054**	-0.042***
	(-1.53)	(-0.74)	(-1.80)	(-2.92)	(-1.31)	(0.51)	(-2.09)	(-2.74)
◇ $D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{IN}}$	-0.057***	-0.076***	-0.083***	-0.073***	-0.027***	-0.051***	-0.046***	-0.033***
	(-5.73)	(-6.89)	(-4.08)	(-5.58)	(-4.57)	(-6.15)	(-3.55)	(-4.15)
◇ $D^{TFP}_{i,t-1} \times \mathrm{CF_{c,t}}^{\mathbf{OUT}}$	-0.083***	-0.091***	-0.159***	-0.148***	-0.042***	-0.044***	-0.100***	-0.075***
	(-5.55)	(-5.22)	(-4.09)	(-6.43)	(-4.32)	(-3.59)	(-4.35)	(-5.48)
Firm Controls$_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1022273	1022273	1022273	1022273	1616184	1616184	1616184	1616184
◇ Intensive changes	852717	852717	852717	852717	856683	856683	856683	856683
◇ Extensive changes	169556	169556	169556	169556	187218	187218	187218	187218
◇ Stay Unlevered	0	0	0	0	572283	572283	572283	572283
Number of firms	222376	222376	222376	222376	328372	328372	328372	328372

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\big(D^{TFP}_{i,t-1}{\times}CF_{c,t}{\times}D^{OUT}\big){+}\gamma D^{TFP}_{i,t-1}{\times}CF_{c,t}{+}\delta_1 D^{TFP}_{i,t-1}{\times}D^{OUT}{+}\delta_2 D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where the dependent variable Ψ is defined in each panel of the table, and is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0, (sample C). $y_{i,t}$ denotes the outstanding financial debt of firm i in year t. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. The right part of the table (i.e., columns 5-8) shows results based on an alternative sample in which the dependent variable Ψ is set equal to 0 when $y_{i,t-1}$ and $y_{i,t}$ are both equal to 0, thus it includes firms in years they stay unlevered. Except for columns 1 and 5 that are estimated using OLS, the rest of the columns are estimated using WLS, where the re-sampling weights are defined as follows: weigth "*ctry×year*" is equal to the inverse of the number of a country's observations in a given year as a share of all observations in that year (i.e. $w_{c,t}{=}N_t/N_{c,t}$); weigths "*empl*" and "*turnover*" are based on the number of employees or turnover, respectively, in each SDBS country-industry(2digits)-size(4 size classes based on the number of employees) class cell to "scale up" the number of ORBIS observations in each cell so that they match those observed in the OECD's SDBS aggregate data. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is evaluated at time t. D^{OUT} denotes an outflow dummy which equals 1 when capital inflows are negative. We multiplied these negative inflows by -1, so that higher CF^{OUT} implies an increase in capital outflows, i.e., non-residents disinvest to a greater extent. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1

Table C.15. Debt Growth and Capital Inflows, Zoom on SMEs and Aggregate Industries

	Zoom on SMEs				Zoom on Aggregate Industries						Industries' EFD		
	SMEs	Micro	Small	Medium	All	Manuf.	Services	Zoom on Services			$D^{EFD}_{s} \times D^{TFP}_{i,t-1} \times$ CF		
								Constr.	Distrb.	Other			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		(11)	
Panel A Dep. var. : $\Delta\ln(y_{i,t})$											High EFD	Low EFD	H-L EFD
$D^{TFP}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$	-0.232***	-0.608	-0.269***	-0.184**	-0.221***	-0.259***	-0.205***	-0.275	-0.315***	0.017	-0.309***	-0.088	-0.221**
	(-4.37)	(-1.10)	(-4.10)	(-2.08)	(-4.44)	(-3.17)	(-3.33)	(-1.57)	(-4.20)	(0.14)	(-4.89)	(-1.05)	(-2.12)
Observations	720533	13968	497644	206822	808105	222955	585149	83007	309193	192947		771691	
% Extensive changes	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%		0%	
Number of firms	164377	4612	118978	40263	180992	46524	134468	19899	68253	46315		172412	
Within Adj. R^2	0.025	0.045	0.027	0.020	0.024	0.023	0.025	0.026	0.023	0.027		0.024	
Dep. var. avg;p50 (in %)	0.3;-4.3	-1.6;-5.8	-0.9;-5.6	3.2;-1.6	0.9;-3.5	2.4;-2.9	0.3;-3.8	1.7;-3.9	1.4;-1.9	-2.2;-7.1		1.1;-3.3	
Panel B Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$											High EFD	Low EFD	H-L EFD
$D^{TFP}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$	-0.339***	0.130	-0.381***	-0.365***	-0.324***	-0.441***	-0.280***	-0.495**	-0.399***	-0.005	-0.416***	-0.196*	-0.220
	(-5.06)	(0.20)	(-4.70)	(-3.13)	(-5.06)	(-3.76)	(-3.67)	(-2.32)	(-4.22)	(-0.04)	(-5.18)	(-1.81)	(-1.64)
Observations	896294	19923	625719	248646	1000333	267601	732732	107203	378656	246873		952077	
% Extensive changes	16.9%	21.8%	17.4%	15.0%	16.6%	14.6%	17.3%	19.4%	15.9%	18.6%		16.4%	
Number of firms	200020	6340	146005	47191	219433	54557	164876	24955	81920	58001		208384	
Within Adj. R^2	0.018	0.031	0.021	0.012	0.017	0.016	0.018	0.019	0.016	0.021		0.017	
Dep. var. avg;p50 (in %)	-1.9;-4.7	-4;-6.9	-2.6;-6	0;-2	-1.6;-4	-0.7;-3.4	-1.9;-4.3	-0.5;-4.3	-1.2;-2.4	-3.5;-7.5		-1.4;-3.8	
Panel C Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$											High EFD	Low EFD	H-L EFD
$D^{TFP}_{i,t-1} \times CF_{c,MAt,t\text{-}2}$	-0.065***	-0.045	-0.069***	-0.062***	-0.064***	-0.059***	-0.065***	-0.062***	-0.083***	-0.034	-0.078***	-0.047***	-0.032*
	(-7.57)	(-0.57)	(-6.44)	(-4.90)	(-7.80)	(-4.41)	(-6.48)	(-2.73)	(-7.20)	(-1.59)	(-8.37)	(-3.01)	(-1.74)
Observations	896294	19923	625719	248646	1000333	267601	732732	107203	378656	246873		952077	
% Extensive changes	16.9%	21.8%	17.4%	15.0%	16.6%	14.6%	17.3%	19.4%	15.9%	18.6%		16.4%	
Number of firms	200020	6340	146005	47191	219433	54557	164876	24955	81920	58001		208384	
Within Adj. R^2	0.050	0.081	0.055	0.034	0.048	0.045	0.049	0.043	0.044	0.057		0.047	
Dep. var. avg;p50 (in %)	1.3;-0.4	1.2;-1	1.2;-0.6	1.5;-0.1	1.4;-0.3	1.5;-0.3	1.3;-0.4	1.4;-0.3	1.4;-0.2	1.1;-0.6		1.4;-0.3	
Firm Controls$_{i,t-1}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		yes	
FE: i,$s\times t$,$c\times t$,$c\times s$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		yes	

Note: This table reports the results of estimating $\Psi=\alpha+\beta\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$, where Ψ is defined in each panel of the table. The regressions in panels B and C jointly estimate the intensive and extensive margin changes in firm-level financial debt $y_{i,t}$. The last column augment our interaction of interest with an industry-level dummy (D^{EFD}_{s}) that equals 1 if an industry's dependence on external finance (EFD), defined in Appendix B.2.1, is greater than the median EFD value across industries, and 0 otherwise. One observation is one firm for one year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-year level and size class level, where size class is decomposed as micro/small/medium/large firms. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to t-2. X is our usual vector of firm controls lagged one year. All regressions are estimated using OLS and include firm, country-industry, industry-year and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.16. Robustness, Alternative Definitions of Firms' Debt Positions (Intensive Margin Changes)

Dependent variable type (y):	Financial Debt **Baseline**	Total Debt	Total Debt (alt. sample)	ST Debt (alt. sample)	LT Debt (alt. sample)
	(1)	(2)	(3)	(4)	(5)
Panel A Dep. var. : $\Delta\ln(y_{i,t})$					
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.276***	-0.315***	-0.367***	-0.316***	-0.195***
	(-5.42)	(-12.56)	(-16.21)	(-12.51)	(-4.29)
Within Adj. R^2	0.024	0.121	0.098	0.069	0.020
Dep. var. avg;p50 (in %)	0.8;-3.5	3.7;1.2	5.4;2.6	5.3;4.2	-1.5;-6.1
Panel B Dep. var. : $\frac{y_{i,t}-y_{i,t-1}}{0.5(y_{i,t}+y_{i,t-1})}$					
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.263***	-0.336***	-0.394***	-0.332***	-0.179***
	(-5.27)	(-13.03)	(-16.90)	(-13.06)	(-4.11)
Within Adj. R^2	0.023	0.123	0.096	0.068	0.020
Dep. var. avg;p50 (in %)	-0.2;-3.5	3.7;1.2	4.7;2.6	4.6;4.2	-2.7;-6.1
Panel C Dep. var. : $\frac{\Delta y_{i,t}}{TotalAssets_{i,t-1}}$					
$D^{TFP}_{i,t-1} \times \mathrm{CF}_{\mathrm{c,MAt,t\text{-}2}}$	-0.053***	-0.207***	-0.245***	-0.183***	-0.014***
	(-6.17)	(-12.33)	(-18.56)	(-15.33)	(-3.18)
Within Adj. R^2	0.044	0.151	0.142	0.112	0.018
Dep. var. avg;p50 (in %)	1.2;-0.5	5.4;0.7	7;1	5.5;1.1	0.6;0
Observations	826217	826217	2248978	2243549	1963149
% Extensive changes	0%	0%	0%	0%	0%
Number of firms	183521	183521	447492	446691	418837
#firms D.TFP (p1;p10;p50)	40;154;968	40;154;968	46;214;1666	46;214;1664	45;207;1633
Firm $\mathrm{Controls}_{\mathrm{i,t\text{-}1}}$	yes	yes	yes	yes	yes
Fixed Effects: i, $s\times t$, $c\times t$, $c\times s$	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi = \alpha + \beta\left(D^{TFP}_{i,t-1} \times CF_{c,MA,t,t-2}\right) + \gamma D^{TFP}_{i,t-1} + \theta_l X^l_{i,t-1} + \alpha_i + \alpha_{c,s} + \alpha_{s,t} + \alpha_{c,t} + \epsilon_{i,t}$. The dependent variable Ψ is defined in each panel of the table and $y_{i,t}$ represents either outstanding financial debt, total debt, total short-term debt or total long-term debt of firm i in year t. The table focuses only on the intensive margin of debt growth since, unlike with financial debt, firms tend to have at all time non-zero current or non-current libabilities. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that is equal to 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median (p50) log-TFP at the country-industry-year and size class (SME, large) level. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to $t-2$. Firm controls X lagged one year include: collateral, firm size, profitability, external financial need, growth opportunities and log-TFP. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table C.17. Robustness, Alternative Capital Inflows Variables (Intensive and Extensive Margins Changes)

Capital Inflows Data Source:	BOP-based			BIS-based				BOP	BIS
Capital Inflows Type:	CF Total Debt **Baseline**	Other Invest.	Total Inflows	ΔXBC all sectors (LBSR)	ΔXBC private (LBSR)	ΔFC private (CBS)	$\Delta LCLC$ private (CBS)	**Supply-driven** $\hat{\lambda}_c\ CF^{\text{World}}$	
Note: reported coefficients multiplied by one standard deviation of CF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Intensive + Extensive Margins									
Dep. var.: $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$									
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,t}}$	-0.940***	-1.064***	-0.474	-0.521*	-0.723**	-1.865***	-1.073***	-2.585***	-1.419***
	(-2.99)	(-3.40)	(-1.53)	(-1.78)	(-2.46)	(-6.16)	(-3.66)	(-9.47)	(-5.53)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-1}}$	-1.924***	-2.096***	-1.255***	-1.262***	-1.372***	-1.756***	-1.392***	-2.450***	-1.081***
	(-5.92)	(-6.42)	(-3.93)	(-4.11)	(-4.45)	(-5.97)	(-4.68)	(-8.00)	(-3.87)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-2.309***	-2.385***	-1.578***	-1.686***	-1.859***	-1.749***	-1.275***	-2.772***	-1.426***
	(-6.80)	(-6.97)	(-4.81)	(-5.30)	(-5.92)	(-6.17)	(-4.36)	(-8.38)	(-4.74)
Panel B: Intensive + Extensive Margins									
Dep. var.: $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$									
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,t}}$	-0.167***	-0.174***	-0.099***	-0.107***	-0.126***	-0.255***	-0.161***	-0.292***	-0.172***
	(-4.42)	(-4.64)	(-2.93)	(-2.99)	(-3.73)	(-6.50)	(-4.46)	(-8.17)	(-4.96)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-1}}$	-0.264***	-0.275***	-0.155***	-0.165***	-0.181***	-0.202***	-0.186***	-0.279***	-0.140***
	(-6.56)	(-6.80)	(-4.12)	(-4.16)	(-4.73)	(-5.40)	(-4.97)	(-7.29)	(-3.88)
$D^{TFP}_{i,t-1}$ × $\text{CF}_{\text{c,MAt,t-2}}$	-0.315***	-0.322***	-0.203***	-0.222***	-0.240***	-0.227***	-0.198***	-0.341***	-0.207***
	(-7.38)	(-7.45)	(-5.15)	(-5.39)	(-6.08)	(-6.24)	(-5.55)	(-8.24)	(-5.18)
Firm $\text{Controls}_{\text{i,t-1}}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Effects: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1022273	1022273	1022273	1022273	1022273	1022273	1012805	1022273	1022273
% Extensive changes	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%	16.6%
Number of firms	222376	222376	222376	222376	222376	222376	221539	222376	222376

Note: This table reports the results of estimating $\Psi{=}\alpha{+}\beta\left(D^{TFP}_{i,t-1}{\times}CF_{c,MA,t,t-q}\right){+}\gamma D^{TFP}_{i,t-1}{+}\theta_l X^l_{i,t-1}{+}\alpha_i{+}\alpha_{c,s}{+}\alpha_{s,t}{+}\alpha_{c,t}{+}\epsilon_{i,t}$, where the dependent variable Ψ is defined in each panel of the table. $y_{i,t}$ denotes the outstanding financial debt of firm i in year t. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median log-TFP at the country-industry-size-year level. *CF* is our country-specific capital inflows variable normalized by its GDP and measured as the moving average from year t-q to t (q=0,1,2). It is defined as follows: in columns 1-3, *CF* is based on BOP data and captures the private total debt inflows, or only the other investment component, or more broadly the total private capital inflows (including equity inflows), respectively; in columns 4-5, *CF* is based on BIS's LBSR data and captures cross-border loans to all sectors, or to the private sector only; in columns 6-7, *CF* is based on BIS's CBS data and captures total foreign claims (in all instruments, to the private sector) or local claims in local currency, respectively; columns 8-9 use the fitted values of world total debt inflows (BOP-based, cf. column 1) or world cross-border banking inflows (BIS-based, cf. column 4). Appendix B.2.2 provides full definitions on BIS-based measures. X is our usual vector of firm controls lagged one year. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.18. Robustness, Alternative Definitions of the TFP Dummy

TFP dummy : years based	$t-1$ & $t-2$	$t+1$ & $t+2$	all t	Baseline			continuous
TFP dummy : cutoff level country-year-...	larger sample; klems; 2 sizes	Baseline		*final sample*; klems; 2 sizes	larger sample; *nace 2dig*; 2 sizes	larger sample; klems; *4 sizes*	n.a.
	Baseline (1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Intensive Margin							
Dep. var.: $\Delta\ln(y_{i,t})$							
$\left\{\begin{array}{l} D^{TFP}_{i,t-1}, \\ TFP_{i,t-1} \end{array}\right\} \times \; CF_{\text{c,MAt,t-2}}$	-0.276*** (-5.42)	-0.314*** (-5.02)	-0.360*** (-7.55)	-0.291*** (-5.80)	-0.277*** (-5.30)	-0.221*** (-4.44)	-0.198*** (-6.21) [-0.223]
Observations	826217	507995	1012873	825904	792854	808105	1019651
% Extensive changes	0%	0%	0%	0%	0%	0%	0%
Number of firms	183521	116644	199835	183486	178510	180992	203169
#firms D^{TFP} (p1;p10;p50)	40;154;968	41;155;936	471;2745;16767	40;148;895	34;88;628	35;89;536	n.a.
Panel B: Intensive + Extensive Margins							
Dep. var.: $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$							
$\left\{\begin{array}{l} D^{TFP}_{i,t-1}, \\ TFP_{i,t-1} \end{array}\right\} \times \; CF_{\text{c,MAt,t-2}}$	-0.459*** (-6.80)	-0.334*** (-4.23)	-0.510*** (-8.29)	-0.470*** (-7.16)	-0.504*** (-7.38)	-0.324*** (-5.06)	-0.334*** (-7.73) [-0.384]
Observations	1022273	619428	1246652	1021929	981872	1000333	1257587
% Extensive changes	16.6%	15.5%	16.7%	16.6%	16.6%	16.6%	16.8%
Number of firms	222376	139180	238804	222355	216579	219433	244185
#firms D^{TFP} (p1;p10;p50)	41;158;1004	41;157;980	484;2819;17290	40;152;908	34;88;639	36;91;549	n.a.
Panel C: Intensive + Extensive Margins							
Dep. var.: $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$							
$\left\{\begin{array}{l} D^{TFP}_{i,t-1}, \\ TFP_{i,t-1} \end{array}\right\} \times \; CF_{\text{c,MAt,t-2}}$	-0.063*** (-7.38)	-0.066*** (-6.62)	-0.070*** (-9.02)	-0.067*** (-7.79)	-0.071*** (-8.19)	-0.064*** (-7.80)	-0.046*** (-7.49) [-0.053]
Observations	1022273	619428	1246652	1021929	981872	1000333	1257587
% Extensive changes	16.6%	15.5%	16.7%	16.6%	16.6%	16.6%	16.8%
Number of firms	222376	139180	238804	222355	216579	219433	244185
#firms D^{TFP} (p1;p10;p50)	41;158;1004	41;157;980	484;2819;17290	40;152;908	34;88;639	36;91;549	n.a.

Note: This table reports the results of estimating $\Psi=\alpha+\beta\big(CF_{c,MA,t,t-2}\times D^{TFP}_{i,t-1}\big)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$, where the dependent variable Ψ is defined in each panel of the table. The construction of D^{TFP} is defined in the table. Instead of a TFP dummy, column (7) uses a continuous measure of firm-level log-TFP. CF is the private debt inflows of country c normalized by its GDP and is measured as the moving average from year t to $t-2$. X is our usual vector of firm controls lagged one year. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.

Table C.19. Robustness, Alternative Productivity Variables (Intensive and Extensive Margins Changes)

Margin Changes & Dependent variable	**Intensive + Extensive** $(y_{i,t}-y_{i,t-1})/(0.5(y_{i,t}+y_{i,t-1}))$					**Intensive + Extensive** $(\Delta y_{i,t})/(TotalAssets_{i,t-1})$				
Productivity Variable	$TFPR$ **Baseline**	$TFPR$ (4-dig. sectors pooled)	LP	$TFPR^C$ (markup adjusted)	MRP^K (markup adjusted)	$TFPR$ **Baseline**	$TFPR$ (4-dig. sectors pooled)	LP	$TFPR^C$ (markup adjusted)	MRP^K (markup adjusted)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: p50										
$D^{TFP}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.459***	-0.405***	-0.182***	-0.373***	-0.141*	-0.063***	-0.052***	-0.021***	-0.075***	-0.089***
	(-6.80)	(-6.00)	(-3.01)	(-4.81)	(-1.86)	(-7.38)	(-6.28)	(-2.92)	(-7.68)	(-9.78)
Observations	1022273	1024777	1010548	877795	911906	1022273	1024777	1010548	877795	911906
% Extensive changes	16.6%	16.6%	16.6%	15.8%	15.8%	16.6%	16.6%	16.6%	15.8%	15.8%
Number of firms	222376	222379	221183	192567	195715	222376	222379	221183	192567	195715
Panel B: p33–p66										
$D^{TFP}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.681***	-0.694***	-0.358***	-0.473***	-0.235**	-0.084***	-0.084***	-0.031***	-0.096***	-0.126***
	(-7.57)	(-7.67)	(-4.09)	(-4.85)	(-2.43)	(-7.58)	(-7.24)	(-2.95)	(-7.97)	(-11.65)
Observations	702332	704351	697152	603267	616348	702332	704351	697152	603267	616348
% Extensive changes	16.5%	16.4%	16.6%	15.8%	15.7%	16.5%	16.4%	16.6%	15.8%	15.7%
Number of firms	169762	168848	170193	146049	148528	169762	168848	170193	146049	148528
Panel C: p25–p75										
$D^{TFP}_{i,t-1}$ × $CF_{c,MAt,t-2}$	-0.834***	-0.777***	-0.468***	-0.690***	-0.219*	-0.111***	-0.104***	-0.039***	-0.124***	-0.145***
	(-7.06)	(-6.70)	(-4.38)	(-5.54)	(-1.76)	(-8.14)	(-7.16)	(-3.07)	(-8.16)	(-11.32)
Observations	501789	504974	497248	434359	444292	501789	504974	497248	434359	444292
% Extensive changes	16.6%	16.5%	16.8%	15.8%	15.5%	16.6%	16.5%	16.8%	15.8%	15.5%
Number of firms	128234	127719	129271	110903	113344	128234	127719	129271	110903	113344
Firm $Controls_{i,t-1}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
FE: i, $s{\times}t$, $c{\times}t$, $c{\times}s$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: This table reports the results of estimating $\Psi=\alpha+\beta\left(D^{TFP}_{i,t-1}\times CF_{c,MA,t,t-2}\right)+\gamma D^{TFP}_{i,t-1}+\theta_l X^l_{i,t-1}+\alpha_i+\alpha_{c,s}+\alpha_{s,t}+\alpha_{c,t}+\epsilon_{i,t}$. The dependent variable Ψ is defined in columns (1-5) as the DHS mid-point growth rate in the financial debt y of firm i in year t, while in columns (6-10), Ψ is computed as the firm's change in debt from the previous period scaled by lagged total assets. One observation is one firm-year between 2003 and 2017 (unbalanced panel). Singleton are dropped. D^{TFP} is a time-varying dummy that equals 1 if a firm i is in the high productivity bin in t-1 and t-2, where the cut-off is defined using the median (p50) productivity in Panel A, the p33-p66 in Panel B, and the p25-p75 in Panel C at the country-industry-size-year level. The productivity measure is defined as the log-TFP in columns 1 and 6 where the production function estimation is performed separately for each country and 2-digit industry, while in columns 2 and 7 the estimation is done for every 4-digit industries. In columns 3 and 8, we use the labor productivity (real VA over cost of employees). Columns 4 and 9 use the revenue log-TFP adjusted from firm-specific markups, and columns 5 and 10 use the marginal revenue product of capital, see Appendices A.2 and A.3 for further details. CF is the private debt inflows of country c normalized by its GDP and measured as the moving average from year t to t-2. X is our usual vector of firm controls lagged one year. All regressions are estimated using OLS and include firm, country-industry, industry-year, and country-year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the industry-year level. ***p<0.01, **p<0.05, *p<0.1.