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The Global (Mis)Allocation of Capital*

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Abstract

The allocative efficiency of capital flows is one of the oldest and most contentious questions. We answer it by matching cross-border securities holdings reported in the US external statistics from 1995 to 2022 with the corresponding firm-level measures of allocative efficiency. We find that US investors tilt their international equity investment toward firms with high MRPK and markups, thereby fostering their potential for growth. Foreign investors tilt their holdings toward US firms with high productivity and intangible capital. A horse race shows that productivity is the best predictor of foreign investment in US firms and MRPK for US investment in foreign firms. Both US and foreign firms that receive more international funding increase spending on intangible capital, and foreign firms also increase tangible capital. The results are stronger for more productive firms.

JEL Classification: E2, F3, F6.
Keywords: productivity, capital allocation, capital flows.

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1. Introduction

Whether international capital flows are directed toward firms with the highest growth potential is a longstanding, contentious issue (see Lucas (1990a), Caselli and Feyer (2007), Gourinchas and Jeanne (2013) among others). This is an important question as countries' growth depends on effectively and efficiently allocating resources and funds to firms (see Restuccia and Rogerson (2008), Hsieh and Klenow (2009)). The answer to this question has been elusive because of difficulties capturing the quantity of international capital directed to firms. External capital flow statistics are readily available at the country and asset class levels, but less so at the firm level. We exploit our access to confidential firm-level securities holdings of international investors to solve this problem and analyze possible drivers of international capital flows and their firm-level effects. Our results provide insights into the role of international investors in boosting growth, and the effects of impediments to those flows such as capital controls and other frictions.

We analyze the role of international capital flows in allocating capital to firms by estimating firm-level productivity and other efficiency measures, and matching them with the securities appearing in surveys of US external claims and liabilities. So far, the few studies on the allocative role of capital flows focused on developing countries and/or flows into individual countries, such as Cingano and Hassan (2022), which provides a direct matching between bank loans and firms' MRPK for Italy. Our study is the first to provide a direct link between international funding and firms' production efficiency resulting from foreign equity investment in the US and US investment abroad, thus capturing a sizable share of global capital movements. Our rich dataset allows us to characterize the allocation process along several dimensions, to make predictive statements on current account dynamics, and to assess the real consequences of capital flows.

Showing an improvement in allocative efficiency amounts to proving that funding allocates to the most productive firms. This is a challenging task as it requires matching highly-disaggregated measures of firms' funding with their wedges. We solve both these technical hurdles, and therefore directly answer the question on the allocative efficiency of capital flows.

The backbone of our analysis is the confidential, security-level dataset of cross-border holdings from the official filings of custodians and investors through the Treasury International Capital (TIC) system.[1] These data have been collected annually since 2003 and less frequently for earlier years, so we use a security filling procedure to extend the data back to 1995. These confidential, security-level data have never been used in this type of study. To assess the allocation effects of capital flows we focus on equities which comprise a substantial share of cross-border capital and can be mapped to individual firms.

The second pillar of our analysis consists of structurally-estimated, firm-level measures of production efficiency and financial conditions using accounting (Compustat Global) and financial (Refinitiv or Worldscope) data. We estimate firms' productivity with Olley and Pakes (1996); other measures of production efficiency such as MRPK and intangible capital; wedges, such as markups[2]; credit risk, which we proxy with Merton (1974) distance to default.[3] After adjusting those measures across countries for comparability, and computing regional production elasticities, we then merge our firm-level measures with the US cross-border investment through an ISIN matching process. Our final dataset spans from 1995 to 2022 and covers roughly 21,000 firms.

Our main empirical analysis is aimed at assessing how each firm's share of cross-border investment, net of the firm's share of total market capitalization – henceforth the net share – maps to the distribution of each productivity and efficiency measure. Evidence of a wide dispersion in firm-level measures and/or a shift in the distribution indicate possible misallocation (see Hsieh and Klenow (2009)). We focus on the net share to measure the allocation that takes place on top and above that driven by changes in market capitalization. We employ a panel specification that links the net share to all our firm measures, and includes firm and time fixed effects to control for unobservable firm characteristics and common time trends. We estimate this specification separately for US external claims and liabilities.

We find that US investors tilt their portfolios toward foreign firms with relatively high marginal productivity of capital and markups, and lower credit risk. Firms with high wedges are smaller

1 Reporters are legally-mandated to complete the TIC SHL/SHLA surveys, and hence are likely to have a higher data quality than voluntary surveys. The returns are regularly cross-checked with commercial data sources to verify their accuracy. More details on the data are provided in Appendix A and A.1.

2 We follow De Loecker et al. (2020).

3 We also consider for robustness other financial indicators such as Sharpe ratios.

than the pareto allocation would recommend, hence allocating international funds to them allows them to grow (see Hsieh and Klenow (2009)). In the other direction, foreign investors weight their portfolios toward US firms with relatively high productivity, intangible capital, and credit risk. The magnitudes of the effects are sizable: a one standard deviation increase in the net share is associated with a 6% higher productivity for US firms. The significance of the production efficiency and wedge measures persists even when we include financial indicators, such as Sharpe ratios. Over time, both the productivity measures and markups of firms held by both US and foreign investors have increased.

Next, we unpack the drivers of this allocation in three ways. First, through a dynamic decomposition of the changes in allocations into the within and between firm components. We find that the between firm component is predominant in the reallocation process, as investors relocate their shares over time toward more productive and efficient firms and firms with higher markups. Second, we ask whether the firm measures hold any predictive power for future capital flows. Through a horse race using on an out-of-sample predictive procedure by Fair and Shiller (1990), we show that all firm measures have high predictive power for changes in net shares, the highest being productivity for US firms and MRPK for foreign firms.

Finally, and most importantly, we assess the real consequences of this international investment by testing whether firms that received more funds in the past also invest more. To capture this we proceed as follows. We estimate, with future projection, a probit model that links the probability of investing either in tangible or in intangible capital to the past positive changes in the net shares. In the tradition of the misallocation literature, as wedges are heterogeneous (see Hsieh and Klenow (2009)), only some firms can use funds efficiently. To capture this heterogeneity and understand which firms are investing, we interact the regressor with a dummy that captures whether firms' productivity is above or below the median. What this specification captures is the pre-determined nature of the funding and how they impact firms choices heterogenously. We find that foreign firms increase their investment in both tangible and intangible capital following an increase in funding from abroad, while US firms appear to boost spending only on intangible capital. The effects are larger for more productive firms.

Our findings contribute to several strands to the literature. First, our results contribute to the misallocation literature (see Restuccia and Rogerson (2008), Hsieh and Klenow (2009) or Baqaee and Farhi (2020) among others), by providing direct evidence on how allocation of funding to firms may improve efficiency. The direct matching of securities and firm measures is pivotal for this. Our results on the reallocation to the most productive firms also speak to the growing evidence on the importance of superstar firms for the macroeconomy (see Autor et al. (2020)).

Second, our results add to a growing literature that connects capital flows to misallocation. Past literature exploited episodes of large capital inflows (see Gopinath et al. (2017), Varela (2018) or Bau and Matray (2023)) and examined their impact on proxies for misallocation. A contemporaneous literature in trade examine how other events affect the distribution of misallocation (see Carrillo et al. (2023)). Our precise matching of cross-border investment to firms' productivity and efficiency measures allows us to document a number of novel facts. We examine in particular how firms receiving positive funds invest compared with those that don't. Cingano and Hassan (2022) is another example of a study with a direct connection between funding, banks' loans in their case, and the MRPK of Italian firms. We greatly extend the scope by focusing on capital flows in and out of the US, the largest connector in the global financial network.

Third, the early literature on capital flows (Lucas (1990b)) argued that capital was not flowing from rich to poor countries despite substantial differences in the marginal return to capital. Subsequent literature emphasized the importance of wedges on domestic investment and savings in stifling returns (Gourinchas and Jeanne (2013); Caselli and Feyer (2007)), or the role of public versus private assets (Aguiar and Amador (2011); Alfaro et al. (2008)). Our findings establish that US investors do invest in foreign firms which are more efficient and have higher markups, consistent with theory. Our study therefore resolves previous puzzles by shifting the focus from countries, for which precise TFP are hard to obtain, to firms.

Finally, our paper contributes methodologically to the growing literature that estimates firms' measures structurally (most of it cited above), as we extend the proxy method by computing regional production elasticities.[4]

4 See Appendix B.2.

2. Econometric Strategy and Data

Our analysis matches US cross-border equity holdings with firm productivity and other measures with three main goals. The first is to examine the allocation of international funding along the distribution of each firm measure. The second is to assess whether firm characteristics have predictive power for future capital flows. The third is to assess how firm investment responds to international capital flows. Below we first describe the data, then the econometric specifications, and then briefly introduce our estimates of the firm measures. More details on data and firm measures are in Appendix A and B.2.

2.1. Data

For our analysis we compile and match two micro datasets. The first consists of a high quality, confidential, security-level dataset of the universe of US external portfolio claims and liabilities. This is constructed from the official filings of custodians and investors through the US Treasury International Capital (TIC) system, collected annually since 2003, and less regularly in earlier years. The filings include the quantity of each foreign security held by a US investor and US security held by a foreign investor, as well as information on their returns.[5] Our analysis focuses on equities as we can map them to individual firms. More details on the dataset are in Appendix A. For country groupings we use firm nationality rather than residence – that is, the nationality of the parent holding company of the issuing firm.

The second pillar of our analysis is a dataset of firm-level productivity and other measures. Specifically, we estimate Olley and Pakes (1996) productivity,[6] MRPK, markups, intangible capital, and Merton (1974) distance to default. To construct these measures we use structural estimations based on accounting (Compustat Global[7]) and financial (Refinitiv) data. We obtain the equity

5 Bertaut et al. (2024) compile and use the same data to re-examine the size of the US excess return on external claims versus liabilities and to decompose its components by asset class.

6 We do so using both revenues and value added and results are robust to both.

7 Compustat Global data were obtained by Ester Faia under the purview of Harvard University licenses while she was visiting that institution. The remaining co-authors, Carol Bertaut, Stephanie Curcuru, and Pierre-Olivier Gourinchas, did not have any unauthorized access to this data while working on this paper/project.

market capitalization of each firm from Worldscope. More details on how we estimate the measures are provided in Section 2.3 and Appendix B.2.

We merge the two datasets with the following steps. The TIC equities are matched to the Worldscope identifiers, which are then matched to the identifiers from all our firm measures. When we divide the securities by sector, we use the Worldscope General Industry Classification. Our final combined dataset covers the time period 1995-2022 and has roughly 21,000 observations. We are able to match most of the TIC data with the corresponding firm measures from Compustat Global data. The share matched on average for all the years in our sample is 80% for US firms and 70% for foreign firms.

2.2. Empirical Specifications

We start by relating the cross-border equity holdings to the firm measures. We aim to detect drivers of differences between the observed allocations and that of a simple allocation based on market capitalization. Therefore our dependent variable is the firm share of the total equity holdings, less the firm share in the total equity market capitalization. Specifically, we construct the share invested in firm i, as $s_i = \frac{h_i}{W}$, where h_i is the holdings of foreign equity security i by US investors, W is the value of all US equity claims which is obtained by summing over securities: $W = \sum_i h_i$. Similarly, h_i^* is foreign holdings of the equity of US firm i, and W^* is total holdings of US equities by foreign investors: $W^* = \sum_i h_i^*$. Next, we define the market share of security i as follows: $\overline{s}_i = \frac{V_i}{V}$, where V_i is the market cap of security i, $V = \sum_i V_i$ is the market capitalization of all stocks (either US or foreign). Everything is measured in US dollars. For much of our analysis the variable of interest is share of security i in the TIC data set, net of its share in total market cap (**net share** in short)

$$\tilde{s}_{i,t} = s_{i,t} - \overline{s}_{i,t} = \frac{h_{i,t}}{W_t} - \frac{V_{i,t}}{V_t}. \tag{1}$$

Baseline Regression. The baseline specification is a panel regression, with firm and time fixed effects, that links the net share of security i to the firm measures:

$$\tilde{s}_{i,t} = \gamma + f_i + f_t + \sum_j \alpha^j x^j_{i,t} + \epsilon_{i,t} \tag{2}$$

where $x^j_{i,t}$ is one of the measures j, for firm i at time t. The firm measures used as regressors are Olley and Pakes (1996) productivity,[8] MRPK, markups, intangible capital, and distance to default. In our baseline regression we include all measures to assess the informative power of each of them. Firm fixed effects control for all unobservable characteristics. The specification therefore shows how investors allocated their portfolio share to each firm based on its observed and unobserved characteristics. Time effects control for specific business cycle trends that effect all firms or for other trends. The regression is estimated on all equity holdings and time periods, separately on equity holdings of US and foreign firms. Estimation is done with robust standard errors, clustered at firm level. The coefficients of interest are the α^j. A positive sign indicates a higher allocation of funding to firms in with relatively high values of each measure.

Within-Between Firms Decomposition. One way to assess the macro implications of the capital flows is to aggregate the firm measures, weighted by their shares in the cross border portfolio, and decompose their changes over time into within and between firm components. If for instance the changes in an aggregate productivity measure are driven primarily by the between firm component, this implies that investors reallocate over time their investment toward firms with higher productivity. If instead aggregate productivity increases, but the within component is predominant, this means that investors keep funding the same firms, whose productivity grows over time. In sum we can assess how much of the change in the aggregate measure over time is due to the contribution of changes in each firms measure, or to the reallocation of investors' portfolios.

8 Our results stand if we use other firm productivity measures, such as Levinsohn and Petrin (2003).

We aggregate each firm productivity and other measures by weighting each individual firm measure by the net share defined earlier:

$$FM_t^j = \sum_i \tilde{s}_{i,t} x_{i,t}^j \tag{3}$$

where $x_{i,t}^j$ is the firm measure j. We then decompose changes in the aggregate into within and between components:

$$\begin{aligned} FM_t^j - FM_{t-1}^j &= \sum_i \tilde{s}_{i,t} x_{i,t}^j - \sum_i \tilde{s}_{i,t-1} x_{i,t-1}^j = \\ &= \underbrace{\sum_i \tilde{s}_{i,t-1}(x_{i,t}^j - x_{i,t-1}^j)}_{\text{within term}} + \underbrace{\sum_i (\tilde{s}_{i,t} - \tilde{s}_{i,t-1}) x_{i,t-1}^j}_{\text{between term}} + \\ &+ \underbrace{\sum_i (\tilde{s}_{i,t} - \tilde{s}_{i,t-1})(x_{i,t}^j - x_{i,t-1}^j)}_{\text{covariance}} \end{aligned} \tag{4}$$

Horse Race: Predictive Power of Firms Measures. The large and growing current account deficit of the US had given rise to a large literature devoted to study its sustainability (see Gourinchas and Rey (2007) among others). The broader ideas relate to the inter-temporal approach to the current account (see Obstfeld and Rogoff (1995)), whereby countries can borrow against the prospect of growing productivity. In this context we ask whether firms' characteristics, as given by our measures, hold any predictive power for future capital flows. To this purpose we run a two stage horse race, using the Fair and Shiller (1990) methodology, to establish if and which of the measures has the largest predictive power for future capital flows.

The methodology consists of two stages. In the first stage we estimate an in-sample (up to 2018) panel regression with the following within firm specification:

$$\tilde{s}_{i,t} = \gamma + f_i + f_t + \sum_{j=1}^{2} \alpha_i^j x_{i,t}^j + \epsilon_{i,t} \tag{5}$$

where $\tilde{s}_{i,t}$ is net share, f_i and f_t are firm and time fixed effects, and each regressor $x_{i,t}^j$ is the measure

j for firm i. We run the panel specification with pairs of measures, considering all combinations. In other words, each of the specifications in eq. (5), with two of the firm measures, represents an econometric model. The second stage assesses the predictive power of each of those models. To implement the second stage we use the estimates from each first stage specification to forecast the firm-specific net share in 2018 and 2022. Equipped with those, we regress the actual change in the firm level net portfolio share onto the ones predicted by each of the first stage models[9]:

$$\tilde{s}_{i,2022} - \tilde{s}_{i,2018} = \xi + \beta_j(\hat{s}^j_{i,2022} - \hat{s}^j_{i,2018}) + \beta_m(\hat{s}^m_{i,2022} - \hat{s}^m_{i,2018}) + \epsilon_{i,2022} \tag{6}$$

where $\tilde{s}_{i,t} - \tilde{s}_{i,t-1}$ is the actual change in net share from 2018 to 2022, and $(\hat{s}^j_{i,2022} - \hat{s}^j_{i,2018})$ are the predicted changes in net share from regressions using firm measures x^j, with an analogous term for firm measure x^m.

Future Growth Prospects. To examine the real effects of international capital flows, we use a state-contingent econometric specification that allows us to examine both how receiving funds effects investment and which firms employ those funds more efficiently. Specifically, we estimate a firm-level probit regression linking future investment, some years ahead, to the change in the net share. To identify the role of capital flows, as opposed to other forces, we interact the net share with a dummy variable that selects firms receiving positive funding. If capital flows from international investors facilitate growth, we should observe an increase in investment when firms receive positive funding. Furthermore, in the tradition of the misallocation literature (see Hsieh and Klenow (2009)), firms have different constraints which impact their ability to use additional funds effectively. We therefore expect the impact of international funding on firm-level investment to differ along the distribution of our firm-level productivity measures, an aspect which we capture by interacting the net share with a dummy capturing whether the firm's TFP is above or below median. Formally, the specification reads as follows:

$$\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0] = \alpha + \beta(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})\mathcal{I}^{TFP_{i,t}}\mathcal{D}^{\tilde{s}^+_{i,t}} + \delta k_{i,t-1} + \epsilon_{i,t} \tag{7}$$

9 Since the firm-level error terms generally have non-zero means, we assume they are equal to the firm-level mean error term over the sample through 2018.

where $\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0]$ is the probability that investment is positive at time horizon n, $(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})$ is the change in the net share, $\mathcal{I}_{TFP_{i,t}}$ is an indicator function for whether the firm TFP is above or below the median, and $\mathcal{D}^{\tilde{s}^{+}_{i,t}}$ is a dummy indicating whether the change in net share was positive. The specification controls for past capital to capture trends. For foreign firms we include region dummies. In the spirit of Cingano and Hassan (2022) the specification aims to identify for which firms higher funding translates into higher growth.

2.3. Structural Estimates of Firms' Productivity, Wedges, and Financial Variables.

In what follows we provide a short description of how we construct the firm measures including productivity and efficiency wedges, such as Olley and Pakes (1996) firm productivity, MRPK, and markups; credit risk, which we proxy by Merton (1974) distance to default. Appendix B.1 provides full details on the estimation methods, focusing in particular on the estimation of the production elasticities, which are a key part of the firms' markup estimates.

We estimate the production elasticities, markups, and the intangibility measures using data from Compustat Global. We rely on this dataset as it has the best match with the TIC securities data set.

MRPK. A measure which encompasses both productivity and efficiency is the marginal productivity of capital, MRPK in short. Under the assumption that firms have Cobb-Douglas production functions, revenues can be written as follows:

$$Revenues_{i,t} = TFPR_{i,t} K_{i,t}^{\alpha_k} L_{i,t}^{\alpha_l} M_{i,t}^{\alpha_m} \tag{8}$$

where K is capital, L is labor, M is intermediate input, and $TFPR_{i,t}$ is the firm-specific unobserved revenue productivity, for firm i. Given the above, $MRPK = \frac{\partial Revenue_{i,t}}{\partial K_{i,t}} = \alpha^k Revenue_{i,t}$. The latter provides a within-industry measure of MRPK, if all firms in an industry k share the same α^k.

Markups. We estimate the markups following the structural estimation approach pioneered in the industrial organization literature (see Hall (1988) or De Loecker and Warzynski (2012)). The general framework relies on using firms' first order conditions, together with accounting data and non-parametric estimates of the production elasticities. The method is based on agnostic assumptions about the form of market competition. The expression for the firm i markup, which is obtained by merging firms' first order conditions for labor and variable inputs, reads as follows:

$$\mu_{i,t} = \frac{\beta_{X_{i,t}}}{S^*_{X_{i,t}}} \tag{9}$$

where $\beta_{X_{i,t}}$ is the output elasticity with respect to any variable input X, which could be either labor or other intermediate inputs, and $S^*_{X_{i,t}}$ is the share in production of the variable input costs.[10] For the production elasticities, $\beta_{X_{i,t}}$, we employ the method envisaged by Olley and Pakes (1996). A challenge faced in our context comes from homogenizing the measures across countries. To this purpose we first adjust all accounting data for CPI. Furthermore, we devise a methodology to estimate regional elasticities, which is often a thorny issue due to lack of data for some country-sector pairs.[11] We compute production elasticities for firms in countries for which we have enough data points, for the remaining ones we assign the elasticities estimated in the closest sector-country pair through a clustering algorithm. Appendix B.1 provides more details on the procedure.

Intangible Capital. We construct a measure of intangible capital based on Selling, General and Administrative (SG&A) expense data using the perpetual inventory method. Intangible capital accumulates as follows:

$$K^I_{i,t+1} = K^I_{i,t} + (1 - \delta^I)K^I_{i,t}\frac{P^I_{t+1}}{P^I_t} \tag{10}$$

10 We use the first order condition for variable input, rather than the one on capital, as the latter may depend on adjustment costs.

11 Loecker et al. (2020) for instance compute markups across the world using the local values for the input share costs, but adopt the same US production elasticity for all countries.

for firm i and where P_t^I is the CPI of each country in local currency.[12] To set eq. (10) in motion, we initialize intangible capital using the perpetual inventory method:

$$K_{i,0}^I = \frac{I_{i,0}^I}{g_{Ind_i}^I + \delta^I - \pi_{Ind_i}^I(1-\delta^I)} \tag{11}$$

where $I_{i,0}^I$ is the investment in organizational capital in the first year of the sample, $\pi_{Ind_i}^I$ is the average price growth in each industry-country pair, and $g_{Ind_i}^I$ is set equal to the average growth rate of SG&A expenditure in the industry. Industries are classified based on the 2-digits NAICS code.[13]. Equation 10 is computed by iterating forward and starting from the initial level of intangible capital.

Credit Risk. We measure credit risk with the Merton distance to default (see Merton (1974)). This is obtained using information on the firm market value of assets and on the value of equity and debt, which we obtain from Refinitiv. The distance to default is derived under the assumption that debt maturities are homogeneous and that the capital structure is such that the value of the firm assets are divided between debt and equity: $V_t^a = D_t + V_t^e$.[14] Using the Black and Scholes formula and Ito's lemma,[15] one can imply the mean and volatility of asset values, which in turn deliver the default threshold. The distance to default is the difference between the expected value of the asset and the default point as follows:

$$D2D_t = \frac{log(\frac{V_t^a}{D} + (r - \frac{1}{2}\sigma_a^2(T-1)}{\sigma_a\sqrt{T-t}} \tag{12}$$

where r is the risk free rate, T is the maturity of the debt, V^a is the value of firm assets, and σ_a is its volatility. A smaller value of $D2D$ indicates that a firm is closer to default.

12 Following Eisfeldt and Papanikolaou (2013) or Peters and Taylor (2017) we set organization capital investment to be equal to 30% of SG&A expenditures.

13 Following Eisfeldt and Papanikolaou (2013) we set δ^I equal to 20%

14 The calculation ignores dividends or coupons; it is assumed that there are no short sales.

15 Asset values are assumed to follow a Geometric Brownian motion.

3. Capital Allocations across Firms.

Before presenting the estimates from our econometric specifications, we present time series and cross-sectional evidence on the relationship between cross-border investment and firm-level measures. We focus on markups in this section. We use kernel densities to examine their relationships over two different time sub-samples. We examine the sample of firms with equities which appear in the TIC datasets. The goal is to assess the presence of misallocation among the firms that receive international funding, and to track its changes over time. Evidence of wide dispersion in firm-level measures and/or a shift in the distribution indicate possible misallocation (see Hsieh and Klenow (2009)).

Figure 1 plots the kernel densities of the markups for the firms that are in TIC over two time periods: 2004-2009 and 2017-2022. Table 1 shows the mean, median and standard deviation of markups for firms in TIC across time samples and sectors.

Figure 1 shows that there is a shift over time toward firms with larger markups for both US and foreign firms. In Figure 2 we report the kernel densities by industry sector. The shift toward higher markups are evident in most sectors. The shifts are large and significant according to Kolmogorov-Smirnov test[16], reported in Table 2 indicating there has been a significant increase in the markups. Both the wide dispersion and shift in the distributions indicate the presence of misallocation (see Hsieh and Klenow (2009)).

The shifts in the distributions are larger for firms that have global appeal and are held cross-border: for instance for the period 2000-2022 the average markups grew from 1.95 to 2.3 for the firms in the TIC data set and from 1.4 to 1.9 for the entire set of firms in Compustat Global. Overall, two main messages emerge from these statistics. First, the dispersion in the markups is evidence of misallocation. Second, the rightward shift in the distribution for the firms in the TIC sample signals a reallocation of international holdings over time to firms with higher markups.

A complementary assessment of the changes in misallocation over time can be done by examining

16 Given the number of observations in our sample, 21,000 firms, the threshold for the D-stat that rejects the null hypothesis of no significant shift is given by $D_{threshold} = \frac{1.36}{(21{,}000^2)} = 0.0030$. Any value larger than that implies that there has been a significant shift in the distribution across the two sample periods.

changes in the markup statistics across the same two time samples. Under the assumptions laid down in Hsieh and Klenow (2009) the markup dispersion is a sufficient statistic for misallocation. The markup statistics, presented in Table 1, show that the mean and median have grown in most sectors for both US and foreign firms. This is due to the general increase in market concentration observed elsewhere. As for the dispersion, it shows a decline for most sectors. This suggests that, for the firms that receive international funding, allocative efficiency may have improved. To provide a more structural assessment of the link between capital flows and allocative efficiency we turn to the results of our empirical analysis.

3.1. Baseline Results: the Allocation of Capital Flows.

Our baseline specification, shown in eq. (2), aims to assess how capital flows have been allocated along the distribution of firms. Results are shown in Table 3. A positive value of α^j signals an allocation to firms with higher values of firm measure j.

For liabilities, the coefficients on all variables are highly significant and precisely estimated. Foreign investors tilt their portfolios toward the most productive US firms and those with relatively high intangible capital and credit risk. The results also show that when investing in US equities foreign investors favor firms that were already highly efficient. The magnitude of the coefficients are economically meaningful: as an example, a 1 standard deviation increase in the net share is associated with a 6% increase in firm productivity or a 2% increase in intangible capital. Based on the coefficients for the panel regressions, this would increase the implied share by 0.0068, a non trivial number given that the mean is 0.0001535.

US investors appear to do the opposite. They weight their portfolios toward less efficient firms with high MRPK, high markups, but low credit risk. These magnitudes are also meaningful: as an example, a 1 standard deviation change in net share is associated with a 4% change in MRPK. By allocating resources to firms with high wedges, US investment may allow those firms to grow and get closer to the pareto frontier. In section 3.4 we examine whether international capital flows lead to an increase in firms' investment.

Finally, in the traditional CAPM portfolio shares are linked to the excess return. It is useful to establish whether the measures that we adopt have information power on top and above classic financial measures. Our regressions already control for market capitalization and for a proxy of credit risk in the form of distance to default. We now test the robustness of the results further by adding the Sharpe ratio, which may proxy excess returns more directly. Results are shown in Table 7 in Appendix B.3. All firms' variables retain similar levels of significance and the same sign. The only significant difference is that the distance to default is now insignificant for US firms, possibly because the two measures provide overlapping information.

3.2. Within-Between Decomposition

A first assessment of the macro implications of the allocation of cross-border investment can be done by examining the changes in firm productivity and other measures over time, and by decomposing it into the within and between firm components. This allows us to track whether the shifts higher in the distributions which we noted earlier are the result of a reallocation of cross-border investment toward the firms with higher productivity and markups, or because cross-border investors held firms whose productivity and markups increased over time.

Figure 3 plots a three-year rolling window of the within-between decomposition for productivity, MRPK, and markups. The between firm component is prevalent for all the measures for both US and foreign firms, comprising more than 80% of the changes in all years. In addition, the between component is mostly positive, which implies that investors shift their holdings toward firms at the top of the distributions of each variable. There is also a notable pattern in the reallocations across firms over time. They are notably positive in the earlier and the later parts of the sample, and small or negative around the time of the 2008-09 global financial crisis.

3.3. Predicting Capital Flows

So far we assessed how investors allocated their cross-border investment across firms. A large and influential literature, starting with the work of Obstfeld and Rogoff (1995) on the inter-temporal approach of the current account, linked current account sustainability to countries' future income and productivity growth prospects. Countries with high expected future growth should be able to borrow more from international investors. In light of this, we ask whether firms' productivity and the other characteristics linked to their future profitability help to predict capital flows.

To assess the usefulness of our measures in predicting capital flows, we run a horse race following the two-stage approach envisaged in Fair and Shiller (1990), and explained in Section 2.2. To recap, in the first stage we estimate an econometric model over the early-sample calibration period, and then use the model to predict net shares for the forecast period. We then run the second stage regression to assess the forecast performance. Table 4 presents the R^2 of the second stage estimates to assess the predictive power of each model. The pairs with the highest R^2 have the largest predictive power.

For US firms, in the top of the table, all pairs have large predictive power, with little difference across the pairs of measures. Productivity, coupled either with markup of MRPK, holds the largest predictive power. For foreign firms, the regressions have less predictive power, likely because the sample includes EM firms which have noisier data. For foreign firms MRPK, coupled with productivity or intangible capital, has the highest predictive power. For the pairs with the highest R^2, the F test for the predicted shares is significant at 1%.[17]

3.4. Real Effects of Capital Flows

Last, we examine whether international capital flows have real effects. We answer this question in two ways. We first investigate whether firms that received more international funding invest more, and next examine which type of firms are more likely to increase investment after receiving additional funding. Indeed, in the tradition of the misallocation literature, heterogeneity in wedges implies that firms' first order conditions for inputs allocate resources differently across firms. Thus only some firms can allocate resources efficiently.

17 Even for foreign firms, whose data are noisier, the overall fit is fairly good; the F test is significant at the 5% when the R^2 is 0.165 or larger, it is at 10% for all other pairs and it's significant at 1% for the 2 pairs with the highest R^2.

Specifically, we estimate the bivariate probit regressions, described in eq. (7) to assess the probability that investment is positive in the future. Explanatory variables are the change in net share, lagged levels of capital, time dummies, and for foreign firms region dummies. Robust standard errors ARE clustered by firm. Because of the widespread decline in labor and capital shares and growth in intangible capital (see Haskel and Westlake (2017), Corrado and Hulten (2010) or Corrado et al. (2022)), we include investment in both tangible and intangible capital as outcome variables.

To identify the role of capital flows we interact the change in net share with a dummy that identifies whether the change was positive. In presence of misallocation firms are not investing equally, as they have different MRPK (see Hsieh and Klenow (2009)). To understand which firms are investing, we interact the change in the net share with a dummy for whether firm productivity was above or below median.

Results are shown in Tables 5 and 6. We show results only for firms for which the net share increased to focus on firms which received capital inflows. Foreign firms who receive funding from US investors increase both their tangible and intangible investment over all three horizons. The investment in relatively large for firms with productivity above the mean at most horizons. In the other direction, US firms do not appear to increase tangible investment in response to foreign funding. However the response of intangible investment is extremely large for firms with above average productivity. This could be driven by firms in quickly growing sectors with large amounts of research and development, like the biotech sector.

4. Conclusions

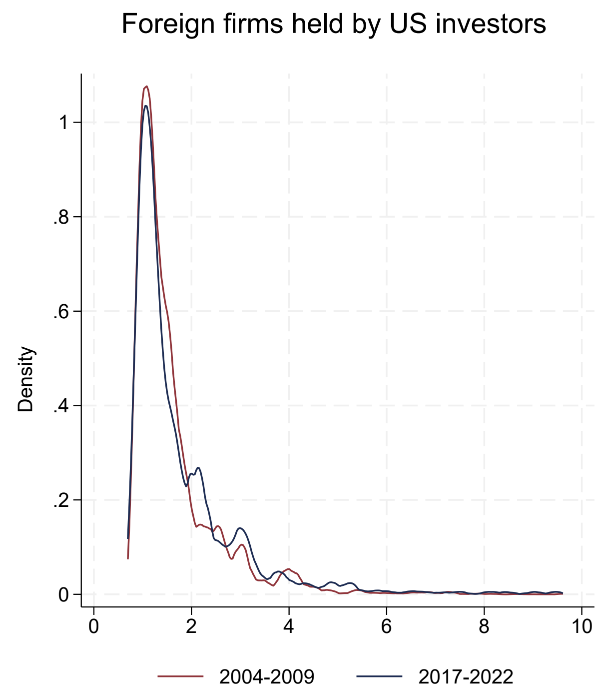
There is growing evidence that the misallocation of resources is a key driver of growth. Financial globalization and the increasing role of the private sector in the global economy has heightened interest in understanding the allocative role of international capital flows and their macroeconomic effects. Our paper is the first to tackle this topic using firm-level cross-border equity allocations in and out of the US, paired with the corresponding firm-level measures of productivity and efficiency.

Our analysis uncovers that all cross-border investment is tilted toward firms at the top of productivity and efficiency distributions, but with different implications. US investors tend to allocate shares to foreign firms facing large wedges; this can foster their growth and increase efficiency. Foreign investors tend to invest more in high productive US firms with high amounts of intangible capital. In addition, firms' measures of production efficiency have a good predictive power for future capital flows, on top and above financial measures.

At last, firms that receive more cross-border funding tend to increase investment. However, in line with the misallocation literature, which emphasizes heterogeneity in production efficiency across firms, only firms with a productivity above median increase their investment.

Our paper adds to the understanding of the misallocation process and how it has evolved. The implications for global capital flows and the evolution of growth and wealth are left for further work.

Figure 1: Markup Distributions: Kernel densities of markups for the firms whose equities are in the TIC data set over two time samples: 2004-2009 and 2017-2022. Securities are matched with markups computed using data from Compustat Global. Markups are weighted by market capitalization share of TIC holdings.



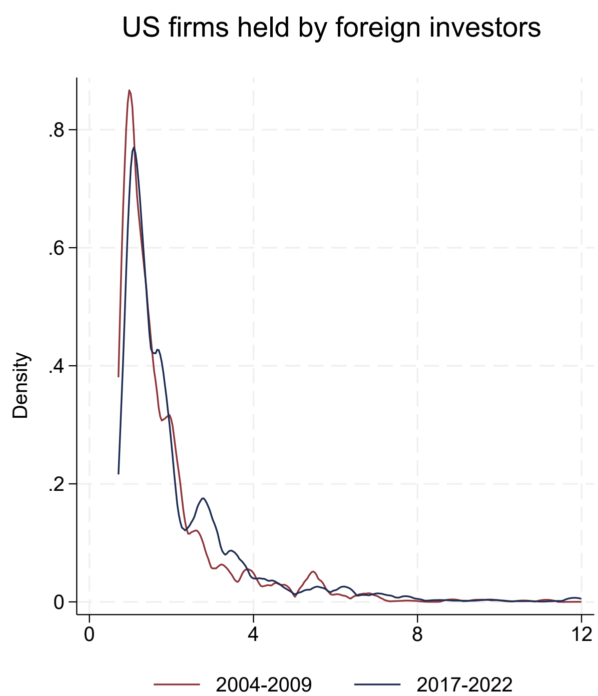


Figure 2: Markup Distributions by Industry: Kernel densities of markups for the firms whose equities are in the TIC data set over two time samples: 2004-2009 and 2017-2022. Securities are matched with markups computed using data from Compustat Global. Markups are weighted by market capitalization share of TIC holdings.

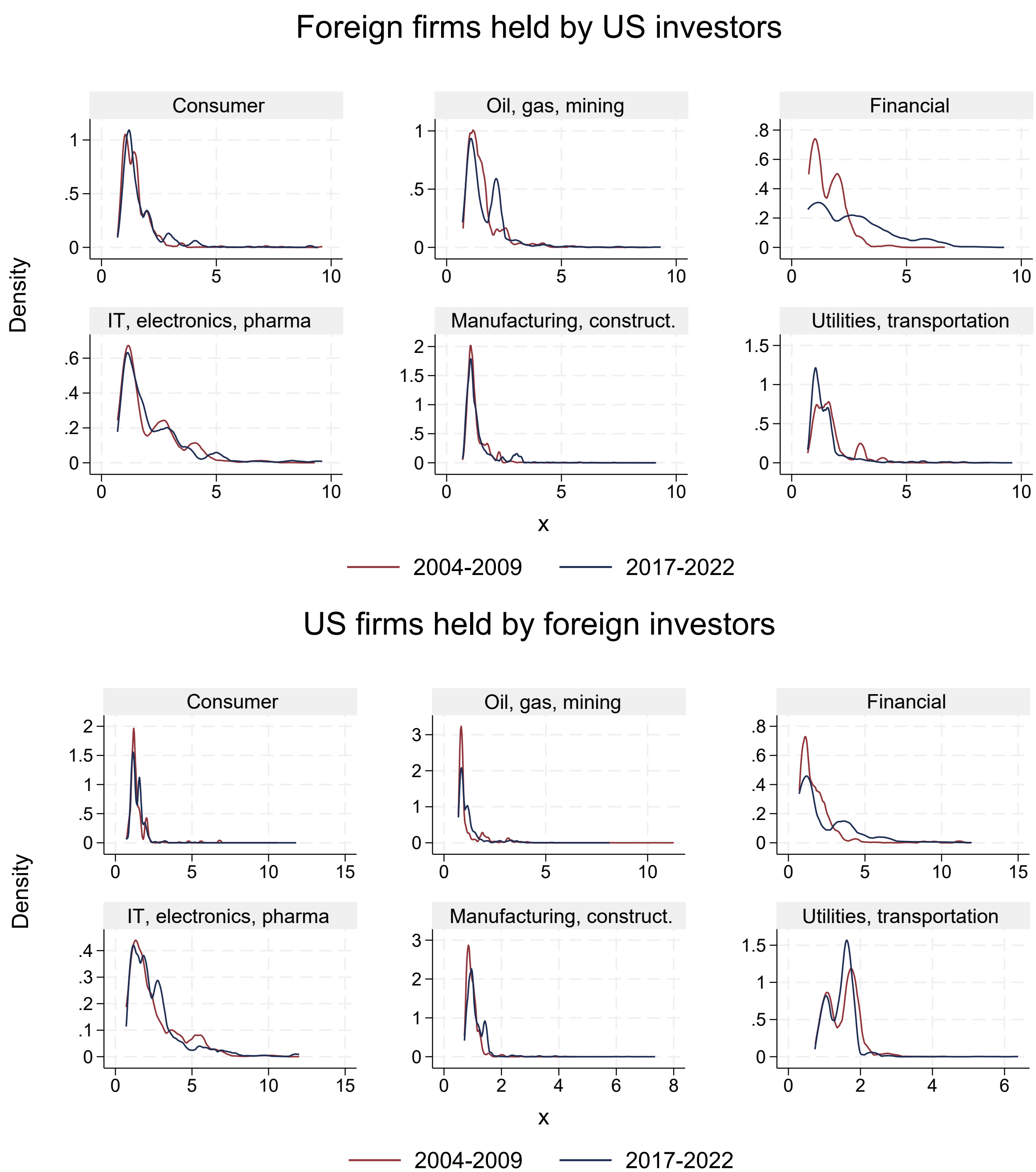


Figure 3: Within-Between Decomposition: Decomposition of changes in aggregate productivity, MRPK, and markups into within, between, and covariance effects. The bars plot the three-year moving average of each component. The aggregate measures are constructed by weighting each firm-level measure by the share of each firm in the TIC data set.

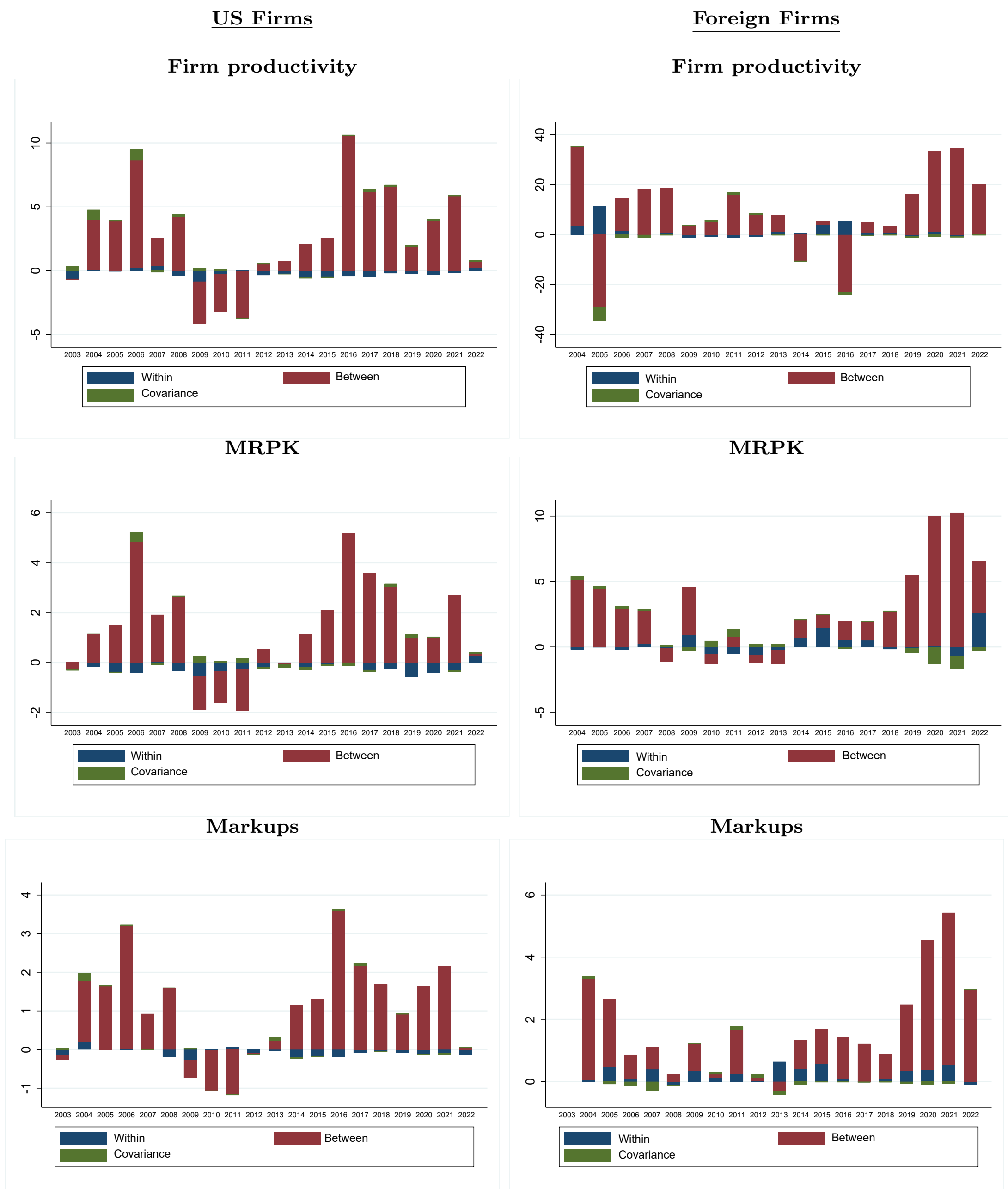


Table 1: Markup Summary Statistics: Markups constructed using elasticities from Olley and Pakes (1996) and firm-level data from Compustat Global. Firms weighted by market capitalization share in the TIC data set.

	Mean					
	U.S. Firms			Foreign Firms		
	1995-2001	2005-2009	2016-2022	1997-2001	2005-2009	2016-2022
Consumer	1.42	1.47	1.41	1.33	1.50	1.69
Oil, gas, mining	1.04	1.18	1.20	1.34	1.48	1.66
Financial	1.54	1.93	2.49	1.25	1.65	2.50
IT, electronics, pharma	2.55	2.53	2.57	1.93	2.14	2.18
Manufacturing, construction	1.14	0.99	1.10	1.20	1.26	1.35
Utilities, transportation	1.48	1.52	1.47	1.46	1.72	1.56
Total	1.84	1.88	2.08	1.52	1.63	1.77
	Median					
	U.S. Firms			Foreign Firms		
	1995-2001	2005-2009	2016-2022	1997-2001	2005-2009	2016-2022
Consumer	1.23	1.27	1.28	1.24	1.36	1.36
Oil, gas, mining	0.87	0.86	0.98	1.23	1.29	1.33
Financial	1.33	1.45	1.49	1.24	1.46	2.32
IT, electronics, pharma	1.94	1.98	2.01	1.50	1.57	1.68
Manufacturing, construction	0.97	0.94	1.00	1.11	1.11	1.12
Utilities, transportation	1.32	1.63	1.52	1.25	1.50	1.30
Total	1.35	1.39	1.55	1.25	1.31	1.34
	Standard Deviation					
	U.S. Firms			Foreign Firms		
	1995-2001	2005-2009	2016-2022	1997-2001	2005-2009	2016-2022
Consumer	0.66	0.85	0.45	0.47	0.80	0.99
Oil, gas, mining	0.55	0.76	0.64	0.52	0.69	0.91
Financial	0.73	1.47	2.02	0.16	0.82	1.58
IT, electronics, pharma	1.87	1.70	1.76	1.12	1.33	1.47
Manufacturing, construction	0.64	0.24	0.40	0.33	0.46	0.70
Utilities, transportation	0.42	0.43	0.38	1.10	0.88	1.01
Total	1.42	1.42	1.58	0.87	0.95	1.16

Table 2: Significance Test of Markup Distribution Shift: Kolmogrov-Smirnov tests for equality of markup distributions over two sample periods, 2004-2009 and 2017-2022. Tests conducted for distribution of markups for firms whose equities are in the TIC data set, constructed using elasticities computed with Olley and Pakes (1996) and data from Compustat Global, by industry sector and weighted by market capitalization share of TIC holdings. Left columns are for US firms and right columns for foreign firms. For the 21,000 firms in our sample the D-stat threshold for significance of the shifts across periods is $D_{threshold} = 1.36/(21,000^2) = 0.0030$

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	U.S. Firms		Foreign Firms	
	D-stat	p-values	D-stat	p-values
All industries	0.0666	0	0.0238	0
Consumer	0.0665	0.002	0.0363	0,.006
Financial	0.3039	0	0.1533	0
Manufacturing and Construction	0.1351	0	0.0417	0
Oil, gas, mining, transportation	0.0577	0.101	0,0544	0,041
IT, pharma and others	0.0567	0	0.071	0
Utilities and transportation	0.0949	0.031	0.0938	0

Table 3: Baseline Regression Results: Estimates of the panel specification $\tilde{s}_{i,t} = \gamma + f_i + f_t + \sum_j \alpha_i^j x_{i,t}^j + \epsilon_{i,t}$ linking firm shares in the TIC data set net of total market capitalization shares to firms' measures j, namely Olley and Pakes (1996) productivity, MRPK, markup, intangible capital, and Merton (1974) distance to default (D2D), with firm and time fixed effects. Regressions are run separately for foreign firms (claims) and US firms(liabilities). Firm measures are estimated using data from Compustat Global adjusted across countries by country CPI. Sample size 21,000 firms, time period 1995-2022. Robust standard errors clustered at firm level.

	α^j, US Firms (liabilities)		
j	Coefficient	t-stat	S.E.
Productivity	0.00223***	3.71	0.00060
MRPK	-0.00090***	-3.35	0.00027
Markup	-0.0032***	-3.11	0.00106
Intangible cap.	0.0000005**	1.11	0.0000005
D2D	-0.00023***	-3.4	0.00006
	α^j, Foreign Firms (claims)		
j	Coefficient	t-stat	S.E.
Productivity	-0.00003	-0.13	0.00023
MRPK	0.00115***	2.28	0.00050
Markup	0.00441***	2.35	0.00188
Intangible cap.	-0.0000005	-0.45	0.000001
D2D	0.00027***	1.69	0.00016

Table 4: Predicting Capital Flows: In the first stage we estimate an in-sample (up to 2018) panel regression with a within firm specification:$\tilde{s}_{i,t} = \gamma + f_i + f_t + \sum_{j=0}^{2} \alpha_i^j x_{i,t}^j + \epsilon_{i,t}$**, where** $\tilde{s}_{i,t}$ **is the portfolio share net of market cap,** f_i **and** f_t **are firm and time fixed effects. The second stage is:**$\tilde{s}_{i,2022} - \tilde{s}_{i,2018} = \xi + \beta_j(\hat{s}_{i,2022}^j - \hat{s}_{i,2018}^j) + \beta_m(\hat{s}_{i,2022}^m - \hat{s}_{i,2018}^m) + \epsilon_{i,2022}$**, where** $\tilde{s}_{i,2022} - \tilde{s}_{i,2018}$ **is actual change in portfolio share from 2018 to 2022 and where** $\tilde{s}_{i,2022}$ **is the portfolio share of firm** i **net of its market cap, and where** $\beta_j(\hat{s}_{i,2022}^j - \hat{s}_{i,2018}^j)$ **are the predicted changes in portfolio share for firm measures** x^j**, with an analogous term for firm measure** x^m**. The table reports the** R^2 **of each second stage regression model.**

	β_j and β_m, US Firms (liabilities)			
	MRPK	Productivity	Intangible Cap.	D2D
Markup	0.5382	0.5506	0.538	0.5417
MRPK		0.552	0.5373	0.5307
Productivity			0.5447	0.5372
Intangible Cap.				0.5372
	β_j and β_m, Foreign Firms (claims)			
	MRPK	Productivity	Intangible Cap.	D2D
Markup	0.1291	0.1241	0.1257	0.1242
MRPK		0.1508	0.1579	0.1287
Productivity			0.1204	0.1282
Intangible Cap.				0.1322

Table 5: Capital Flows and Tangible Investment: Estimated coefficient of a bivariate probit regression: $\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0] = \alpha + \beta(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})\mathcal{I}^{TFP_{i,t}}\mathcal{D}^{\tilde{s}^+_{i,t}} + \delta k_{i,t-1} + \epsilon_{i,t}$, where $\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0]$ is the probability that tangible investment is positive at time horizon n, $(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})$ is the change in the net share, $\mathcal{I}_{TFP_{i,t}}$ is an indicator function for whether the firm TFP is above or below the median, and $\mathcal{D}^{\tilde{s}^+_{i,t}}$ is a dummy indicating whether the change in net share was positive; only results for positive $\mathcal{D}^{\tilde{s}^+_{i,t}}$ are shown. Dependent variable is growth in investment on tangible capital over 2, 3, or 4 years. For foreign firms we include region dummies. Robust standard errors, clustered by firm. Firm productivity is computed through Olley and Pakes (1996) using Compustat Global data. Estimated over 1995-2022.

	Foreign Firms (claims)		
	Two years	Third year	Fourth year
Above Median TFP	0.46***	0.50***	0.53***
z-stat	(3.64)	(3.70)	(3.74)
Below Median TFP	0.29***	0.38***	0.47***
z-stat	(2.25)	(2.81)	(3.25)
	U.S. Firms (liabilities)		
	Two years	Third year	Fourth year
Above Median TFP	-1.09**	0.08	-0.41
z-stat	(-1.9)	(0.1)	(-0.47)
Below Median TFP	0.56	0.34	1.82
z-stat	(0.66)	(0.38)	(1.41)

Table 6: Capital Flows and Intangible Investment: Estimated coefficient of a bivariate probit regression: $\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0] = \alpha + \beta(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})\mathcal{I}^{TFP_{i,t}}\mathcal{D}^{\tilde{s}^{+}_{i,t}} + \delta k_{i,t-1} + \epsilon_{i,t}$**, where** $\Phi_{i,t}[k_{i,t+n} - k_{i,t+n-1} > 0]$ **is the probability that intangible investment is positive at time horizon** n**,** $(\tilde{s}_{i,t} - \tilde{s}_{i,t-1})$ **is the change in the net share,** $\mathcal{I}_{TFP_{i,t}}$ **is an indicator function for whether the firm TFP is above or below the median, and** $\mathcal{D}^{\tilde{s}^{+}_{i,t}}$ **is a dummy indicating whether the change in net share was positive; only results for positive** $\mathcal{D}^{\tilde{s}^{+}_{i,t}}$ **are shown. Dependent variable is growth in investment on intangible capital over 2, 3, or 4 years. For foreign firms we include region dummies. Robust standard errors, clustered by firm. Firm productivity is computed through Olley and Pakes (1996) using Compustat Global data. Estimated over 1995-2022.**

	Foreign Firms (claims)		
	Two years	Third year	Fourth year
Above Median TFP	0.75***	0.77***	0.70***
z-stat	(4.12)	(3.93)	(3.28)
Below Median TFP	0.52***	0.66***	0.79***
z-stat	(3.16)	(3.77)	(4.12)
	U.S. Firms (liabilities)		
	Two years	Third year	Fourth year
Above Median TFP	5.86***	6.26***	5.56***
z-stat	(5.34)	(5.37)	(4.56)
Below Median TFP	0.91	0.91	0.60
z-stat	(0.93)	(0.99)	(0.57)

References

Aguiar, Mark and Manuel Amador, "Growth in the Shadow of Expropriation," *The Quarterly Journal of Economics*, 2011, *126* (2), 651–697.

Alfaro, Laura, Sebnem Kalemli-Ozcan, and Vadym Volosovych, "Why doesn't capital flow from rich to poor countries? An empirical investigation," *The Review of Economics and Statistics*, 2008, *90* (2), 347–368.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Baqaee, David Rezza and Emmanuel Farhi, "Productivity and misallocation in general equilibrium," *The Quarterly Journal of Economics*, 2020, *135* (1), 105–163.

Bau, Natalie and Adrien Matray, "Misallocation and capital market integration: Evidence from India," *Econometrica*, 2023, *91* (1), 67–106.

Bertaut, Carol, Beau Bressler, and Stephanie Curcuru, "Globalization and the Reach of Multinationals Implications for Portfolio Exposures, Capital Flows, and Home Bias," *Journal of Accounting and Finance*, 2021, *21* (5), 92–104.

_ , Stephanie Curcuru, Ester Faia, and Pierre-Olivier Gourinchas, "New Evidence on the US Excess Return on Foreign Portfolios," *International Finance Discussion Papers 1398*, 2024.

Carrillo, Paul, Dave Donaldson, Dina Pomeranz, and Monica Singhal, "Misallocation in Firm Production: A Nonparametric Analysis Using Procurement Lotteries," *NBER working paper No. 31311*, 2023.

Caselli, Francesco and James Feyer, "The Marginal Product of Capital," *The Quarterly Journal of Economics*, 2007, *122* (2), 535–568.

Cingano, Federico and Fadi Hassan, “International Financial Flows and Misallocation: Evidence from Micro Data,” *CEPR Discussion Paper No. DP17186*, 2022.

Corrado, Carol A and Charles R Hulten, “How do you measure a “technological revolution”?,” *American Economic Review*, 2010, *100* (2), 99–104.

Corrado, Carol, Jonathan Haskel, Cecilia Jona-Lasinio, and Massimiliano Iommi, “Intangible capital and modern economies,” *Journal of Economic Perspectives*, 2022, *36* (3), 3–28.

Doraszelski, Ulrich and Jordi Jaumandreu, “Measuring the bias of technological change,” *Journal of Political Economy*, 2018, *126* (3), 1027–1084.

_ and _ , “Using cost minimization to estimate markups,” *Available at SSRN 3496603*, 2019.

Eisfeldt, Andrea L and Dimitris Papanikolaou, “Organization capital and the cross-section of expected returns,” *The Journal of Finance*, 2013, *68* (4), 1365–1406.

Fair, Ray C and Robert J Shiller, “Comparing information in forecasts from econometric models,” *The American Economic Review*, 1990, *80* (3), 375–389.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, “Capital allocation and productivity in South Europe,” *The Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Gourinchas, Pierre-Olivier and Helene Rey, “International financial adjustment,” *Journal of Political Economy*, 2007, *115* (4), 665–703.

_ and Olivier Jeanne, “Capital flows to developing countries: The allocation puzzle,” *Review of Economic Studies*, 2013, *80* (4), 1484–1515.

Hall, Robert E, “The relation between price and marginal cost in US industry,” *Journal of political Economy*, 1988, *96* (5), 921–947.

Haskel, Jonathan and Stian Westlake, *Capitalism without Capital: The Rise of the Intangible Economy*, Princeton University Press, 2017.

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Levinsohn, James and Amil Petrin, "Estimating production functions using inputs to control for unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Loecker, Jan De and Frederic Warzynski, "Markups and firm-level export status," *American Economic Review*, 2012, *102* (6), 2437–71.

— and Jan Eeckhout, "Global market power," *NBER working paper No. 24768*, 2018.

— , — , and Gabriel Unger, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Lucas, Robert, "Why Doesn't Capital Flow from Rich to Poor Countries?," *American Economic Review*, 1990, *80* (2), 92–96.

Lucas, Robert E., "Why Doesn't Capital Flow from Rich to Poor Countries?," *The American Economic Review*, 1990, *80* (2), 92–96.

Merton, Robert C, "On the pricing of corporate debt: The risk structure of interest rates," *The Journal of Finance*, 1974, *29* (2), 449–470.

Obstfeld, Maurice and Kenneth Rogoff, "The intertemporal approach to the current account," *Handbook of International Economics*, 1995, *3*, 1731–1799.

Olley, G Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–97.

Peters, Ryan H and Lucian A Taylor, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 2017, *123* (2), 251–272.

Restuccia, Diego and Richard Rogerson, “Policy distortions and aggregate productivity with heterogeneous establishments,” *Review of Economic Dynamics*, 2008, *11* (4), 707–720.

Varela, Liliana, “Reallocation, competition, and productivity: Evidence from a financial liberalization episode,” *The Review of Economic Studies*, 2018, *85* (2), 1279–1313.

A. Treasury International Capital Data: TIC and Measures of Returns

Overview of the TIC system. The TIC (Treasury International Capital) system collects data on US cross-border banking and securities positions and transactions. These data form the basis for the Bureau of Economic Analysis (BEA)'s official US balance-of-payments and international-investment-position data on portfolio investment, and are also used in the Federal Reserve's Financial Accounts data (Z.1 release) on rest-of-world portfolio positions and flows, and in the IMF's Coordinated Portfolio Investment Survey (CPIS).

Responsibility for the TIC system is shared by the US Treasury, the Federal Reserve Bank of New York, and the Federal Reserve Board of Governors. The Treasury oversees the TIC system and publishes a wide variety of tables and reports. The Federal Reserve Bank of New York is responsible for the primary collection and review of the data, and the Federal Reserve Board of Governors is responsible for additional data review, data adjustments, and production and dissemination of TIC tables and reports. Board of Governors staff with direct oversight and responsibility for TIC production have access to much more detailed breakdowns of the data than are available in published form, and much of the data used in this paper rely on these unpublished breakdowns.

The TIC reporting system consists of multiple forms that collect data at varying frequencies and degrees of aggregation. The dataset used in this paper is primarily drawn from the annual surveys, which collect data at the security level on US residents' debt and equity claims against foreign residents (that is, foreign securities held by US residents) and on US debt and equity liabilities to foreign residents (that is, US securities held by foreign residents). Liabilities surveys are conducted each year at the end of June; claims surveys are conducted at the end of December. Data are collected from US-resident custodians, issuers and end investors. TIC annual securities reports and data-collection forms are available at the Treasury Department's TIC website: https://www.treasury.gov/resource-center/data-chart-center/tic/Pages/fpis.aspx.

The data are available publicly at aggregated level at this link. Specifically the dataset reports the break down of the claims and liabilities per equity, debt, Treasuries and officials covering all countries in the US network of capital flows. The data also contain break down per investor type.

In principle the data covers a period that starts at around 1973. However a consistent reporting has been achieved only in more recent years. Hence our sample for this part starts in 1995.

A.1. Further Details on Data Accuracy. Cross-Border Securities Holdings from TIC Annual Surveys

The foreign securities holdings of US residents (claims) and the US securities holdings of foreign residents (liabilities) are collected by the US Department of Treasury in annual Treasury International Capital (TIC) surveys. Survey response is required by law under the authority of the International Investment and Trade and Services Survey Act and Executive Order 11961 of January 19, 1977. Data reported by individual respondents cannot be publicly disclosed and can only be shared with other Federal agencies. Aggregate data may be disclosed only in a manner which will not reveal amounts reported by individual respondents. The data collection is performed by the Federal Reserve Bank of New York, with additional validation by the Federal Reserve Board. Aggregate information by asset class and country is passed to the Bureau of Economic Analysis (BEA) for use in the US International Investment Position and Balance of Payments.

Claims. The annual TIC SHC form collects detailed security-by-security data on the foreign securities holdings of US residents. This data has been collected for December 31, 1997, December 31, 2001, and annually as of December 31, since 2003. The report form and instructions for the claims survey is available at https://ticdata.treasury.gov/resource-center/data-chart-center/tic/Documents/shca2022in.pdf. Reporting institutions for US claims include US-resident custodians and end investors such as financial and non-financial bank and financial holding companies; pension fund managers; managers and administrators of mutual, hedge, and other funds; private equity and venture capital funds; insurance companies; foundations; university endowments; trusts and estates. Institutions must report securities issued by foreign resident organizations in the United States or abroad, including subsidiaries of US -resident organizations, and securities issued by international and regional organizations. Securities should be reported based upon the country of residence of the issuer of the securities. Reportable securities include equities and related assets such as ADRs, and both short- and long-term debt securities including asset-backed securities. Firms must report a security ID (CUSIP), description, issuer name, security type, currency, type of US owner, fair value, number of shares, and the country of residence of issuer.

Liabilities. The annual TIC SHL form collects detailed security-by-security data on the US securities holdings of foreign residents. This data has been collected for December 31, 1994, December 31, 1997, March 31, 2000, and annually as of June 30 since 2002. The report form and instructions for the liabilities survey is available at https://ticdata.treasury.gov/resource-center/data-chart-center/tic/Documents/shla2020in.pdf. Reporting institutions for US liabilities include US-resident custodians, including brokers and dealers and US central securities depositories, and US-resident issuers. Institutions must report all US securities they hold in custody for the account of foreign residents including their own foreign branches, subsidiaries, and affiliates. These securities must be reported by the US-resident custodian even if the securities are in turn held at DTC, Euroclear, or another central securities depository. US-resident issuers must report all securities issued by US-residents which are not held at a US-resident custodian or central securities depository. Firms must report a security ID (CUSIP), description, issuer name, security type, currency, type of US owner, fair value, and number of shares.

Data Validation and Additional Security Details. The Federal Reserve Bank of New York and the Federal Reserve Board validate the price of each security reported on the surveys by comparing them against security prices provided by an outside source such as Bloomberg. Additional information such as dividends, market capitalization, interest payments, and bond maturity are also obtained from an outside source.

B. Appendix on Firm Measures

B.1. Structural Methods for the Estimates of Productivity and Markups

The conceptual framework behind the estimation of the firm-level productivity and the markups is firm cost minimization. The firm first-order conditions are used along with accounting data to estimate production elasticities as well as wedges. Below we describe the conceptual framework in detail.

Firm j produces output Q_{jt} in period t with any capital, K_{jt}, and freely variable amounts of labor and materials, L_{jt} and M_{jt}, with the production function:

$$Q_{jt} = Q^*_{jt} exp(\epsilon_{jt}) = F(K_{jt}, exp(\omega_{Ljt})L_{jt}, M_{jt})exp(\omega_{Hjt} + \epsilon_{jt}) \tag{13}$$

where ω_{Ljt} is labor-augmenting productivity (this follows the extension envisaged by Doraszelski and Jaumandreu (2018) and Doraszelski and Jaumandreu (2019)) and ω_{Hjt} is the Hicks-neutral productivity. As for the variable inputs, the literature typically assumes that they are chosen according to planned production, Q^*_{jt}. The difference between production and planned production is given by shocks that were unanticipated to the firm at the time of choosing the inputs. Defining $VC_{jt} = W_{jt}L_{jt} + P_{Mjt}M_{jt}$ as the variable cost, where $W_{jt}L_{jt}$ is the cost of labor and $P_{Mjt}M_{jt}$ is the cost of variable input, the firms' cost-minimization problem reads as follows:

$$\begin{aligned} &Min_{L_{jt},M_{jt}} = W_{jt}L_{jt} + P_{Mjt}M_{jt} \\ &s.to Q^*_{jt} = F(K_{jt}, exp(\omega_{Ljt}L_{jt}), M_{jt})exp(\omega_{Hjt} + \epsilon_{jt}). \end{aligned} \tag{14}$$

Upon defining the Lagrange multiplier on the constraint as λ_{jt}, we obtain the following first-order conditions:

$$W_{jt} = \lambda_{jt} \frac{\delta F(K_{jt}, exp(\omega_{Ljt})L_{jt}, M_{jt})exp(\omega_{Ljt} + \omega_{Hjt})}{\delta L_{jt}} \tag{15}$$

and

$$P_{Mjt} = \lambda_{jt} \frac{\delta F(K_{jt}, exp(\omega_{Ljt})L_{jt}, M_{jt})exp(\omega_{Hjt})}{\delta M_{jt}}. \tag{16}$$

The above conditions, as well as the envelope theorem, imply that $\lambda_{jt} = MC_{jt} = \frac{\delta VC_{jt}}{\delta Q_{jt}}$. Using the ratio of the first order conditions with the production functions we get the demand for variable inputs:

$$M_{jt} = M(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})P_{Mjt}}, \frac{Q^*_{jt}}{exp(\omega_{Hjt})}) \tag{17}$$

and

$$L_{jt} = L(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})P_{Mjt}}, \frac{Q^*_{jt}}{exp(\omega_{Hjt})})exp(\omega_{Ljt}). \tag{18}$$

Substituting these equations demand into the objective functions delivers the following variable costs:

$$VC_{jt} = VC(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*}{exp(\omega_{Hjt})}) \tag{19}$$

This implies that the marginal cost is:

$$MC_{jt} = \frac{\delta VC_{jt}}{\delta Q_{jt}} = VC(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*}{exp(\omega_{Hjt})}) \tag{20}$$

Since $\lambda_{jt} = MC_{jt} = \frac{\delta VC_{jt}}{\delta Q_{jt}}$ as per envelope theorem, we can re-write equations 15 and 16 as: $\frac{1}{MC_{jt}} = \frac{\frac{\delta Q_{jt}}{\delta L_{jt}}}{W_{jt}}$ and $\frac{1}{MC_{jt}} = \frac{\frac{\delta Q_{jt}}{\delta M_{jt}}}{P_{Mjt}}$ respectively, and where MC_{jt} is the marginal cost based on planned output. The latter imply that the conditions for the marginal productivity of every marginal dollar must be the same in every use. Multiplying the last expression for the marginal cost for labor for the average cost at planner output delivers: $\frac{AVC_{jt}}{MC_{jt}} = \frac{\frac{L_{jt}\delta Q_{jt}}{Q^*_{jt}\delta L_{jt}}}{\frac{L_{jt}W_{jt}}{VC_{jt}}}$. Finally, by defining $\beta_{L,jt} = \frac{L_{jt}\delta Q_{jt}}{Q^*_{jt}\delta L_{jt}}$ as the elasticity of production to labor and $S_{L,jt} = \frac{W_{jt}L_{jt}}{P_{jt}Q^*_{jt}}$ as the share of labor input bill in variable cost we can rewrite the first order condition as follows:

$$\mu_{jt} = \frac{\beta_{jt}}{S_{L,jt}} \tag{21}$$

and where we have set $\frac{AVC_{jt}}{MC_{jt}} = \frac{1}{\mu_{jt}}$, namely the inverse of the elasticity of the variable cost with respect to output. We can derive the expression in 21 also using the first order condition for variable input.

Operationally to estimate the markups the researcher has to choose an input without adjustment costs, estimate its production elasticity, $\hat{\beta}_{X,jt}$ (where X can be either labor or variable inputs), provide an estimate of the error in observed output $eps\hat{i}lon$ and the markup is then computed as follows:

$$\hat{\mu}_{jt} = \frac{\beta_{jt}}{S_{L,jt}} exp(-\hat{\epsilon}_{jt}) \tag{22}$$

The presence of the error in observed output arises from the assumptions behind the estimation of the production elasticities. We estimate production elasticities following Olley and Pakes (1996).

Extending the Method to Compute Regional Production Elasticities. Recent work by De Loecker and Eeckhout (2018) also computes markups globally. To compute markups worldwide, De Loecker and Eeckhout (2018) use the US elasticities per sector and vary the denominator, namely the cost share of variable inputs. They argue that elasticities are largely similar across countries and within sectors and that their interest lies in uncovering time trends. Our goal on the contrary is to provide an exact mapping between the returns and the local firm characteristics. For this reason we extend the procedure by estimating local elasticities. Specifically, production function estimation is carried out for cells that interact two-digit industries and macro-regions. Macro-regions are defined following the detailed UN classification (e.g. Europe is partitioned into Southern, Eastern, Northern and Western Europe), with the exception of Latin America (which groups the UN-denominated regions of South America, Central America and Caribbeans) and Africa (which groups the UN-denominated regions of Northern, Western, Eastern and Southern Africa). The choice of this geographical level and the further aggregation for Africa and Latin America is driven by the trade-off between the preference for representative production function, which pushes for a finer partition, and the need for enough observations to generate high-quality estimates, which calls for further aggregation. Furthermore we deflate the variable input cost shares by the price deflator per each sector region to reduce mis-measurement errors.[18] Further details on the data and computations are reported in appendix B.2.

B.2. Data Used for Estimation of Firm Measures and Wedges

We obtain balance sheet measures from Compustat Global for the period 1990-2022 for net sales, wage cost, Property, Plant and Equipment - Net of Depreciation, Operating Income (before Depreciation and Amortization), Capital Expenditures, Selling, General and Administrative Expenses, Salaries and Benefits Expenses. These balance sheet variables have a yearly frequency and are expressed in local currencies. Each variable is thus converted in US dollars and deflated; data on exchange rates and price deflators (CPI) are taken from the World Bank, with the notable exception of Australia and New Zealand, whose price indexes are downloaded from OECD. Then, the natural logarithms of the real variables are used for the production function estimation - to be precise, to feed the *prodest* Stata command developed by Rovigatti.

Country Grouping for Regional Estimation. Production function elasticities are estimated by sector. For some country-sector pairs the number of observations is not large enough for the production function estimation (see De Loecker and Eeckhout (2018). For this reasons most authors use in all cases the elasticities estimated for the US As we are matching with international data one of our goal is to provide the closest possible measurement of local production conditions. We therefore estimate regional elasticities by grouping in country-sector pairs. The country group that we apply is shown in the plot:

Elasticities are then always computed in two ways, either using specific country sectors (hence dropping the pairs for which there are not enough observations), or per country-sector grouping. In all cases we compare the numbers to the ones estimated in US sectors to assess the plausibility of the magnitudes.

Matching Between TIC and Firm Identifiers. The matching between TIC securities and firm identifiers passes through the Worldscope identifier as in Bertaut et al. (2021). Specifically we

18 Price deflator per region and sector are obtained from the World Bank.

first apply a cross-walk from gvkey in Compustat and Worldscope identifiers. We then match the latter with the ISINs or CUSIP of the TIC securities. First we apply an exact matching on the identifiers, next to improve the coverage we apply a fuzzy matching using firm company name and addresses.

B.3. Other Empirical Results

Table 7: Baseline Regression Results: Estimates of the panel specification $\tilde{s}_{i,t} = \gamma + f_i + f_t + \sum_j \alpha_i^j x_{i,t}^j + \epsilon_{i,t}$ linking firm shares in the TIC data set net of total market capitalization shares to firms' measures j, namely Olley and Pakes (1996) productivity, MRPK, markup, intangible capital, Merton (1974) distance to default (D2D), and Sharpe ratio, with firm and time fixed effects. Regressions are run separately for foreign firms (claims) and US firms(liabilities). Firm measures are estimated using data from Compustat Global adjusted across countries by country CPI. Sample size 21,000 firms, time period 1995-2022. Robust standard errors clustered at firm level.

	α^j, US Firms (liabilities)		
j	Coefficient	t-stat	S.E.
Productivity	0.00259	0.77	0.000887
MRPK	-0.00067***	-2.76	0.000381
Markup	-0.00320***	-3.11	0.00106
Intangible Cap.	0.00072***	1.75	9.39E-07
D2D	0.00031***	2.92	0.000305
Sharpe ratio	-0.00735***	18.01	0.000408
	α^j, Foreign Firms (claims)		
j	Coefficient	t-stat	S.E.
Productivity	-0.00006	0.004	-0.25
MRPK	0.00120***	2.44	0.00051
Markup	0.00440***	2.32	0.0019
Intangible Cap.	-0.00000	-0.37	1.02E-06
D2D	-0.000007***	-0.04	0.000168
Sharpe ratio	0.00400***	8.38	0.000481