The Global (Mis)Allocation of Capital*

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Abstract

Leveraging a unique confidential dataset of the universe of U.S. asset holdings abroad and foreign holdings of U.S. assets, we find that U.S. assets earn a positive excess return of 1.8 percent, on average. This outperformance is explained by asset composition, with claims weighted toward higher-returning equities. Portfolio equity returns are similar across countries, but bond returns are lower in U.S. liabilities than in claims. We find that international securities, relatively and contrary to domestic portfolio investment, are allocated to the top of the firm MPK, intangible and Sharpe ratio distribution. The reallocation to the top of claims is stronger and directed mostly toward Asian firms, tax havens, and firms in BioTech, which in turn grow more. A dynamic within-between decomposition of the portfolio MPK shows that reallocation to the top accounts for 80% to 90% of the changes in the portfolio MPK and has increased over time, pointing to a selection channel. A *horse race* among competing pairs of measures also indicates that MPK, TFP and intangible capital have good predictive power for capital flows. Our evidence uncovers a new allocative role for capital flows, also reconciling previous puzzling findings on the link between capital flows and productivity.

Keywords: securities data, excess return, MPK, intangible capital, market and financial wedges, misallocation, financial centers, allocative efficiency.

* The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or the IMF. We thank Mark Aguiar, Matias Covarrubias (discussant), Nobu Kiyotaki, Morten Ravn, Helene Rey, Alan Taylor, Chris Waller and Tony Zhang for useful comments and seminar/conference participants. Ester Faia acknowledges financial support form the DFG grant agreement FA-1022-3-1. Access to the TIC confidential dataset was granted through access from Federal Reserve Board staff. We thank Alexander Hillert for suggestions on the matching with historical company names of Refnitiv, FactSet, Compustat and Worldscope. Contacts: faia@wiwi.uni-frankfurt.de, carol.bertaut@frb.gov, stephanie.e.curcuru@frb.gov, pog@berkeley.edu

1. Introduction

As wealth and corporate rents become increasingly concentrated and, along with asset values, grow much faster than world GDP, the question of how capital and returns are allocated globally has regained prominence. We leverage a unique dataset of the universe of U.S. claims and liabilities to examine the excess return between the two[1], drilling down to the most dis-aggregated level. A key aspect of our study is the matching of the security holding shares and their returns with firm level measures, such as marginal productivity of capital (MPK since now on) or wedges, which we estimate structurally using heterogenous firm optimization conditions. This allows us to examine the allocation of capital flows along the firm distribution of MPK and other wedges.

Our results progressively move from uncovering facts for aggregate, asset class and security level portfolio returns and shares. We find that the portfolio return differential between claims and liabilities (also dubbed excess return since now on) is persistently positive at around 1.8. This is due to the composition of U.S. claims which are tilted toward equities. The latter account steadily for more than 70% of portfolio claims for all years since 1995 to 2020. When examining the returns at the asset class level, we find instead that equity portfolio returns are equalized across countries. Bond portfolio returns are lower for U.S. liabilities than claims, more so vis-a-vis regions with high sovereign risk. The net between equity claims and bond liability returns over the period 2005-2020 is around 5.27, hence well in line with the equity premium. Next, we examine the allocative roles of capital flows by matching our securities shares with firm MPK, market and financial wedges, and intangibility, which we estimate structurally based on heterogenous firm optimizing conditions, as well as financial wedges. We find that international equity shares, net of market capitalization, are allocated to firms with high MPK, markups, intangible capital and Sharpe ratios, while the relation is reversed for domestic ones, and the effect is stronger for claims. Through a horse race we also find that some measures, such as MPK, TFP and intangible also have good predictive power for capital flows. The reallocation to the top for U.S. claims is stronger for firms located in Asia and in sectors like BioTech. Those facts taken together uncover a new

1 See Gourinchas and Rey (2007) and Curcuru et al. (2008).

role for capital flows in terms of improving allocative efficiency. Based on the insights of the misallocation literature (see Baqaee and Farhi (2020b) or Autor et al. (2020) among others) initial dispersion in MPK or other wedges signals misallocation, with firms at the top of the wedge distribution being smaller than an efficient plan would command. We find that the allocation of international flows toward them increases their growth, hence it reduces the distance with the pareto frontier.

A crucial part of our analysis rests on a highly disaggregated dataset obtained from the official reporting by investors that forms the backbone of the Treasury International Capital (TIC) data collection system.[2] These confidential, security-level data have never been used in this type of study and are available at annual frequency for the time sample 2005-2020.[3] We further extend the data back to 1995 by matching with Refinitiv returns and prices. This implies that any pattern we uncover holds for almost three decades.[4] The data include all securities in claims and liabilities and allow us to compute the portfolio-level returns from the capital gains, the dividend/coupon payments of the individual securities and the amount of each security held. The securities can also be matched through firm identifiers to several measures of firms' characteristics, capturing market, production and financial structures which we estimate structurally using data from Refinitiv, Global Compustat and Worldscope[5].

We start by revisiting the excess return, also distinguishing per type of asset and examining both short run and long run movements. Traditionally the returns were estimated through a top down approach consisting in inferring them from aggregate foreign asset positions reported in the Balance of Payments or through aggregate market indexes such as MSCI (since now on we refer to those as the BEA and the index method).[6] Our security-level data allow us to compute these returns precisely.

To get a sense of the difference we compare our security-level returns with those constructed from aggregates. At the level of aggregate portfolio returns the three methods deliver broadly

2 Reporters are legally mandated to complete the TIC SHL/SHLA surveys, and hence are likely to have a higher data quality than voluntary surveys. More details on the data are provided in Appendix A.

3 Modern SHL surveys are conducted yearly since 2003.

4 The returns are regularly cross-checked with commercial data sources to verify their accuracy. See Appendix A.1.

5 An early matching of TIC with Worldscope is in Bertaut et al. (2021).

6 See Gourinchas and Rey (2007) and Curcuru et al. (2008).

similar messages, with some differences between the BEA and index methods which are based on aggregates and the security-level method arising in the post-crisis period. The difference is due to the high volatility of certain securities and the high prevalence of floating rate and foreign currency-denominated U.S. debt, which are not well represented by aggregate indexes.[7] Across the three methods, we find that the average differential between claims and liabilities has remained positive at around 1.8. The dynamic returns on both equities and bonds appear to be slightly larger and more volatile in the security method. Also the average return differential between equity claims and bond liabilities over the period 2005-2020 is 5.27 in the security method and 4.50 in the BEA-method. In both cases it is close to the classical equity premium. This observation, coupled with the fact that we observe a steady share of equities in the U.S. claims at an average (over the time sample) of 75%, makes us conclude that the overall excess return is largely due to the composition of U.S. claims which is tilted toward equities. Some deterioration of the excess return is observed in the post-financial crisis period when the return on U.S. equity values increased and during the sample period of the European sovereign crisis, when U.S. Treasuries acquired an even larger insurance role. We then compute the long run portfolio returns using several de-trending methods, namely moving averages, Hodrick Prescott, and Hamilton (2018). The long run portfolio returns on equities are roughly equal across countries and hence do not account for the excess return. On the contrary the bond portfolio returns appear lower in U.S. liabilities compared to claims, more so vis-a-vis regions with high sovereign risk, but it is on the rise.

In the next step we decompose the geography of the portfolio returns, also per asset class. For this decomposition we also apply a nationality correction, obtained by matching with constituents information at the level of each and every security.[8] We find that U.S. investors increasingly earn relatively high returns on Asian firms, mostly through the Caribbean financial centers. Over the period 2005-2020 U.S. investors earn 12% on Asian equities and around 9% on European equities, against the 9% earned by foreign investors on U.S. firms. The U.S. bond convenience yield is still visible, but primarily vis-a-vis countries with high

7 The BEA uses indexes when computing valuations for reporting in the International Investment Position.

8 The distinction of issuer residence and nationality is obtained at security level through the constituent information provided in MSCI indexes or information on parent company provided by Moody's Investors Services. The matching is done with text analysis, mirror data and in some cases with manual matching. See Bertaut et al. (2019) or Bertaut et al. (2021).

sovereign risk: on average, over the usual sample period, U.S. Treasuries pay a return of 3.7% against a 6.2% for Asian ones and a 3.9% for European ones.[9]

While the aggregate or regional portfolio returns provide information on the direction of the wealth shifts across countries, only the securities data allow researchers to study the allocative role of capital flows by linking individual shares to issuer characteristics. We therefore leverage on a unique feature of our data and link the securities to firm characteristics, such as MPK and wedges: this also provides a novel perspective relative to the previous literature on the excess return, which tended to focus on investors' preferences rather than issuer characteristics, though the first are notoriously hard to measure. To this purpose we estimate structurally firm MPK, intangibility index, firm TFP, market wedges and financial wedges using firms optimization conditions and match them with the securities data.[10]

We first document a shift forward in the distribution of several measures, such as MPK, TFP, mark-ups. While this is true both for all firms in Compustat and Worlddscope and for those in TIC, the shift in the second is more pronounced. This already suggests that international securities have a prominent allocative role. Chinese firms, as well as firms in retail and BioTech sectors, exhibit some of the largest shifts forward.

Next, to test the allocative role of capital flows more formally, our main econometric strategy relies on regressing the security level equity holdings, net of the market capitalization, on the firm measures. The netting allows us to identify the reallocation of the flows, based on firm characteristics, on top and above the one dictated by market portfolio indeces.[11] We run our regressions both for each individual firm measure and also in a panel that controls for firm, time and region fixed effects. To identify the role of international securities we compare the allocation of equity funds along the firm distribution between international and domestic shares.

We find that equity shares in both claims and liabilities are allocated to firms with higher

9 For total bond returns the difference is less marked. U.S. bonds pay on average 4.4%, Asian 5.9% and European 5.0%.

10 For the estimates we used data from both Global Compustat and Worldscope. The first however produces a much wider overlap with TIC securities, which are geared toward large firms. See Bertaut et al. (2021) for previous matching of the TIC securities with Worldscope. More details on the structural estimates are contained in Appendix B, where we also describe the numerous robustness checks.

11 For this estimation we rely on the nationality of the security, something which allows us to impute the exact direction of the capital flows.

MPK, relatively to domestic shares which instead tend to reallocate to the bottom. The coefficients of the relation are significant and the economic magnitude meaningful: for instance for liabilities, for which the mean equity share is 0.21, a one standard deviation increase in MPK implies a 3.97266 estimated increase in the portfolio share of the corresponding firm. For claims the estimated increase is 2.4. The magnitude are even larger for firm level TFP, for which there is an estimated increase in equity share of 4.2 for liabilities and of 17.11 for claims. The reallocation to the top of claims is again stronger for firms located in Asia or operating in sectors like BioTech. In turn those firms grow more: as an example foreign firms in BioTech saw an increase in the growth of market capitalization from 12.5% on the period 2004-2009 to 17,8% in the period 2014-2109. Note that our results for reallocation to the top hold also when we examine a panel specification that includes firm, region and time fixed effects.

Dispersion in firm characteristics and wedges signals mis-allocation relatively to an efficient allocation that would command equalization of resources. Firms with higher wedges also tend to be smaller than the efficient allocation would command. The allocation of capital flows at the top boosts growth of those firms, hence reducing the distance with the pareto frontier. Efficiency is improved by assigning more resources to best performers.

The allocation of international equity holdings to best performers prompts the question on the allocative role of capital flows relative to domestic ones. We indeed examine the relation between domestic equity shares and firm distribution: strikingly the relation is reversed in this case. This result confirms the allocative role of international capital flows and helps to reconcile previous puzzling findings on the connection between capital flows and MPK (Lucas (1990) or Caselli and Feyer (2007) among others). Our paper does find such a connection by shifting the focus onto firms, as opposed to countries, for which MPK or wedges may be hard to measure.

To provide a coherent narrative that combines the joint evidence of an exorbitant privilege for U.S, investors and of the allocation of shares toward best performers, we also examine the relation between excess equity returns (net of market capitalization) and firm wedges, focusing on mark-ups. This also allows us to quantify the pass-through of firm wedges onto

equity returns. We find that this too is positive and more pronounced for U.S. investors. Not only U.S. investors prefer equities, but they also allocate their shares to firms with high mark-ups and Sharpe ratios. The combination of the two contributes to explain the micro origins of the privilege.

Recent literature has often linked firms with high MPK to their intangible capital (see Covarrubias et al. (2020),Crouzet and Eberly (2021).). We therefore examine the allocation of shares along the intangible distribution. Firms with high intangible have typically high growth prospect, hence the allocation of funding toward them should foster allocative efficiency. We find that equity shares in claims do so, while those in liabilities do not, prompting at the better allocative role of the first.

Next, we examine the allocative role of capital flows along the distribution of financial wedges, a question which connects to the original motivating evidence of the misallocation literature (see Hsieh and Klenow (2009)). We measure financial wedges with distance to default, a measure which proxies credit frictions.[12] We find that both equity shares in claims and liabilities allocate to firms with lower distance to default, hence higher probability of default. Through the lens of the misallocation literature the result implies that international securities help to ease domestic credit constraints, hence reducing the misallocative role of financial wedges. Seen through the lens of a classical portfolio choice optimization however this result may appear puzzling at first as it may imply that investor shares are higher for riskier firms. The optimality of the portfolio shares however is to be judged based on the overall mean-variance optimization. As noted earlier when buying international securities investors may likely seek equities with higher returns, and this may come along with higher market risk. When regressing international equity shares on Sharpe ratios we find a positive relation for American investor, a result which provides further ground to the exorbitant privilege.

So far our results indicate that a reallocation to the top holds in the long run, but it is of interest to examine also its dynamic patterns. We do so in two modes. First, we examine the time trends of the capital reallocation through rolling windows of the **within-between firms decomposition** of the MPK measure. We find that the between component, or else shifts of

12 See Ottonello and Winberry (2020)

shares across firms, is the largest for both claims and liabilities and accounts always for 80% to 90% over the sample period 1995-2020. The between reallocation has also increased for claims and decreased for the liabilities. Second, we examine the predictive power of our firm measures for the allocation of capital flows over time. We do so by running a *horse race* (see Fair and Shiller (1990)) of competing models each based on a subset of our firm measure. Specifically we regress actual changes in equity share between 2015 and 2020 on predicted changes estimated up to 2015 on several combinations for the pairs of firms measures. Overall MPK, TFP and intangible show the highest predictive power for both liabilities and claims.

Taken together these facts confirm at global level the arguments put forward by a literature studying misallocation (see Baqaee and Farhi (2020b)). An early literature (see Hsieh and Klenow (2009)) argued that increasing variation in firm MPK is associated with wedge heterogeneity and as such it induces misallocation of capital. Further developments (see Baqaee and Farhi (2020a) or De Loecker and Warzynski (2012)) uncovered a reallocation to the top of firm wedge distribution (see or Autor et al. (2020) or Gutiérrez and Philippon (2019).) and examined its theoretical foundations. The core mechanism underlying this trend lies in the Marshall's "second law of demand", according to which consumers will be more price inelastic at higher levels of the consumption index. Firms producing those goods can charge higher mark-ups and as such they are smaller. Generally speaking all firms featuring higher wedges tend to be smaller than the pareto allocation would command. We find that international securities, contrary to domestic ones, are allocated to those firms and boost their growth prospects. Given this spirit the paper closer to ours is Bau and Matray (2023) that examine how equity flows to India improved misallocation: while they exploit variation within a natural experiment, we exploit variation across domestic and foreign portfolio shares.

Literature Review. An important literature advanced the idea that much of U.S. global imbalances had to be studied in relation to the valuation channel, namely the change in value of the foreign asset positions. At aggregate level this is also related to the returns' differentials across countries. Pioneering papers have been Gourinchas and Rey (2007), Gourinchas and Rey (2014), Gourinchas et al. (2019) or Eichengreen (2011). Those paper along others (Obstfeld and Rogoff (2005), Meissner and Taylor (2006) and Lane and Milesi-Ferretti (2004))

deduce the aggregate return differentials from the changes in net foreign asset positions, which are then further decomposed in transaction and valuation changes. Since now on we will refer to this procedure as the BEA method. Recently Atkeson et al. (2022) adopt the BEA method to study recent trends of the privilege: they document a recent erosion and attribute it to the out-performance of the U.S. stock market. We do compute the valuation in BEA and in our securities data and discuss the comparison.

Works by Curcuru et al. (2008) and Curcuru et al. (2011) computed returns using indeces and highlighted the importance of distinguishing per type of assets, equities versus debt, as the composition may play a significant role in explaining the return differential. In that context the authors also argued in favour of using return data as opposed to the BEA net foreign asset positions which are affected by some timing imputation[13] and other components with no specific assignment. This literature together with Gourinchas and Rey (2007) have also stressed the importance of distinguishing temporary movements from long run trends, as many of the changes observed in the valuation components maybe temporary.

We move a step forward by using security level administrative data. Those have two advantages. First they improve accuracy in the measurement of the returns. Second, their dis-aggregated nature allows researchers to match with other issuer characteristics and delve into the determinants of the portfolio investment and returns. Our study can also control for the contribution of financial center, another thorny issue, by providing an adjustment of the issuer nationality using the methodology in Bertaut et al. (2019). This too contributes to the correct assignment of the ultimate source of the returns.

Our work is also related to the growing literature that studies the role of firms' dynamic, productivity, wedges and misallocation for the aggregate economy. Following the argument put forward by Hsieh and Klenow (2009) and more recently by Bau and Matray (2023) we measure firm MPK and examine the allocation of capital along the MPK distribution: higher dispersion signals mis-allocation. However reallocation to the top reduces the distance with the pareto frontier: see for instance Baqaee and Farhi (2020b), Autor et al. (2020) among others. Our structural estimate of the market wedges using firm optimizing conditions

13 This refers in particular to the asymmetric adjustment between the flow and the stock positions which creates a difference between the valuation channel measured through aggregate net foreign asset positions and the returns' differentials measured through more granular data.

links our paper to a growing literature employing the production method to identify wedges: see De Loecker and Warzynski (2012), De Loecker and Eeckhout (2018), Doraszelski and Jaumandreu (2018) among others.[14] Our findings on the reallocation to the top link our paper to an expanding literature studying the rise of superstar firms and its implications for macro trends (see Autor et al. (2020)). Methodologically we also extend the production method by computing production elasticities at regional level.[15] Our finding that capital flows are directed toward firms with higher MPK resolves a previous contentious issue in the literature examining whether capital flows are allocated to more productive countries (see Lucas (1990), Caselli and Feyer (2007), Gourinchas and Jeanne (2013) among others.). Our study shifts the focus from countries to firms.

2. Dynamic and Geography of Return Differentials

One measure of global wealth shifts are the returns on external claims and liabilities and their differentials. The literature so far has inferred these returns primarily from the evolution of foreign asset positions. A unique feature of our data is that we are able to compute cross-border returns from the underlying securities collected by the TIC surveys. Those provide highly confidential information from official reporting[16], hence also highly reliable. The time series dimension of the data also allows us to examine the short run and long run determinants of the wealth allocation across countries. To illustrate the importance of using the security-level data we provide estimates of the returns calculated using the traditional methods of inferring them from the U.S. IIP and from standard market indexes of returns. We start by examining the dynamic of returns for claims, liabilities, and their differentials and then move to returns by asset class – equities and bonds. The asset class detail allows us to control for the role of the equity premium and to analyze the differences in compositions between claims and liabilities. At last, note that for calculations of portfolio returns we focus on the time period of the modern surveys, 2005-2020, as the frequency is higher and as such

14 An alternative method has been proposed and pursued by Gutiérrez and Philippon (2016), Covarrubias et al. (2020).

15 More details are provided in Appendix B.

16 The U.S. requires this reporting to both American investing abroad and foreigners investing in U.S. securities.

it is best suited to discuss dynamics. Later on when matching with firm measures we will use an extended time sample going back to 1995.

Portfolio and asset returns are computed by weighting the return of each security in the portfolio of claims and liabilities by the share held. For instance the return on portfolio p (for example, U.S. equities held by foreigners in a specific country/region) is the time series average of the sum of the products of lagged asset weights and current returns:

$$r_p = \sum_{j=1}^{N} w_{j,t-1}^{p} r_{j,t}^{p} \tag{1}$$

where $w_{j,t-1}^{p}$ is the portfolio weight for asset j at the end of period $t-1$, hence they are pre-determined relatively to returns, and $r_{j,t}^{p}$ is the period t return on asset j in portfolio p, and N is the number of assets (countries) in the portfolio. The weighting is of course important as investors typically do not maintain fixed portfolios shares, that is to say that they adjust the quantities in response to changes in values and preferences. In several cases we will also show the average over time, which reads as follows: $\overline{r}_p = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N} w_{j,t-1}^{p} r_{j,t}^{p}$. Finally, the same measure can be computed on the portfolio per asset class.

The returns and their differentials are computed in four different ways. In the first, which we call the security-level, we weight each individual security return by the share invested in that security. In the second we instead use returns of MSCI equity and similar bond indexes at the country-level weighted by the share invested in each country. For the third estimate we infer the returns using the method of early literature that computes them from the wealth and income components of the U.S. BOP and IIP from the Bureau of Economic Analysis (BEA henceforth). Note that BEA obtains the aggregate portfolio holdings from the TIC dataset computed at the date of the official reporting, that is June for liabilities and December for claims. However BEA releases the aggregate shares in December: between the survey date and the date of publication BEA applies adjustments for subsequent liabilities price moves and different estimates of the capital gains component of the moves (see details in Appendix A.1). We consider both types of BEA adjustments in our analysis. The comparison across those methods is crucial to understand possible differences linked to accuracy of the measure, and puts results of earlier work in perspective. Our official data by security are

bound to deliver the best accuracy. The security-level portfolio returns may deviate from the ones computed with the BEA aggregate wealth statistics due to measurements errors in the valuation calculations, particularly those related to the item tilted "other components" (see Appendix A.1 for details.). The security-level may deviate from the index-based ones if the actual holdings of international investors differ meaningfully from those in major indexes.

Dynamic of Claim and Liability Returns and Differentials. Table 1 provides averages of the portfolio returns across the four methods, Table 2 computes the returns across methods and across sub-samples. Several considerations emerge. First, the return over the full sample period is similar across the three methods and ranges from 1.7 to 1.8. The largest difference emerges with the BEA-raw method that does not adjust for the "other components" mentioned above.[17] Second, the cut across sub-sample presented in Table 2 shows that the excess return is positive in period of booms and negative after the financial crisis and at around the European sovereign crisis. This is consistent with the exorbitant duty view according to which U.S. Treasuries provide an even larger insurance to the rest of the world in times in which sovereign risk deteriorates elsewhere (see Gourinchas and Rey (2022)).

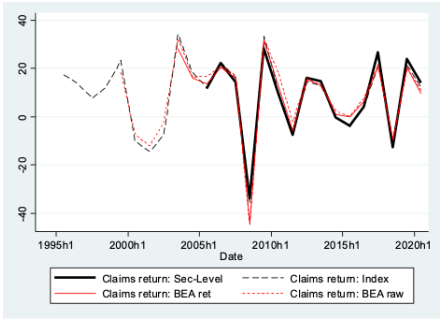
Next, figure 1 plots returns for claims (top and middle left panel), liabilities (top and middle right panel) and the differential between returns on claims and liabilities (bottom panels). It also compares the dynamic with the long run, measured with Hodrick Prescott filter. The time sample differs across method, and the security-level and index liabilities returns are July-June to match the liabilities survey dates. Thus the differential calculations are based on average of current and following year liabilities return. All other returns are by calendar year. More details are in Appendix A.

17 A similar ranking is obtained when using the unbalanced sample 1995-2020 shown in Table 9 in Appendix C.

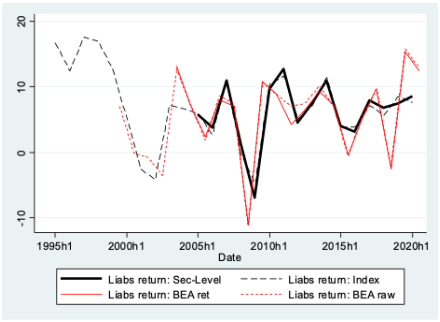
Table 1: **Comparison of average portfolio returns over 2005-2020 across four methods. Security-Level uses the returns by security; Index applies broad total returns indexes from MSCI or bond return sources to the holdings. The BEA ret – uses the valuation adjustments from BEA IIP table 1.3 plus the income from BEA transactions table 4.1; BEA raw estimates the valuation adjustments from the difference in positions in BEA IIP table 1.2 less the flows from BEA Transactions table 1.2 plus the income from table 4.1. Security-level and index liabilities returns are July-June to match liabilities survey; BEA returns are by calendar year. Differentials, which are returns on claims minus returns on liabilities, are based on average of current and following year liabilities returns for the security-level and index methods.**

	Security-Level	Index	BEA ret	BEA raw
Claims return	7.97	7.78	7.65	8.82
Liabilities return	6.11	6.05	5.82	6.20
Return differential	1.77	1.68	1.83	2.62

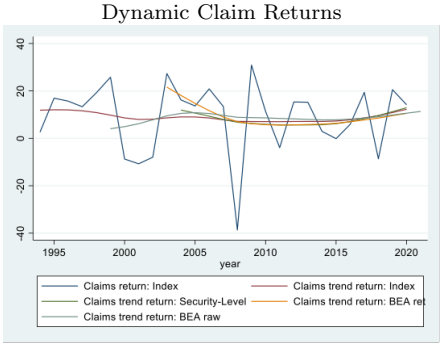
Figure 1: **Returns on claims (left panel) and liabilities (right panel) and differentials (bottom panels) calculated by each of the four methods. First two panels shows dynamics of claims and liabilities, middle panels compare trend (computed with Hodrick-Prescott filter, smoothing parameter of 6.25) and dynamics, bottom panels compare trend and dynamic differentials. The sample length varies by method due to data availability. Security-level and index liabilities returns are July-June to match liabilities survey, and the corresponding differential calculations, which are returns on claims minus returns on liabilities, are based on average of current and following year liabilities returns.**



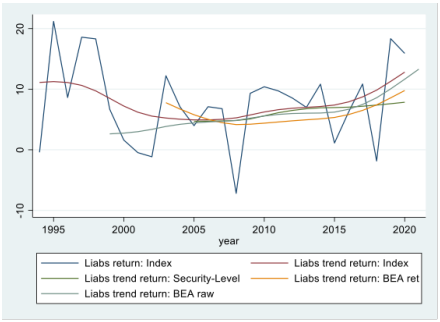
Dynamic Claim Returns



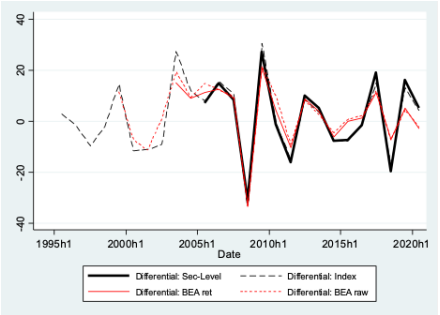
Dynamic Liability Returns



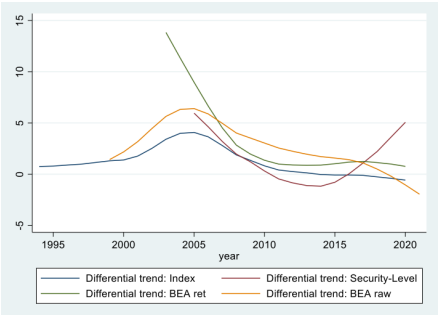
Dynamic and HP Trend, Claims



Dynamic and HP Trend, Liabilities



Dynamic Differential



HP Trend Differential

The dynamics for the claims appear pretty similar across methods, albeit the BEA methods delivers slightly more volatile returns. The divergence across methods is larger for liabilities in the post financial crisis period, likely because foreign investors hold a lot of U.S. bonds denominated in foreign currencies and floating rate bonds. Those are typically excluded from U.S. focused return indexes, and floating-rate bonds are less volatile that fixed rate bonds.

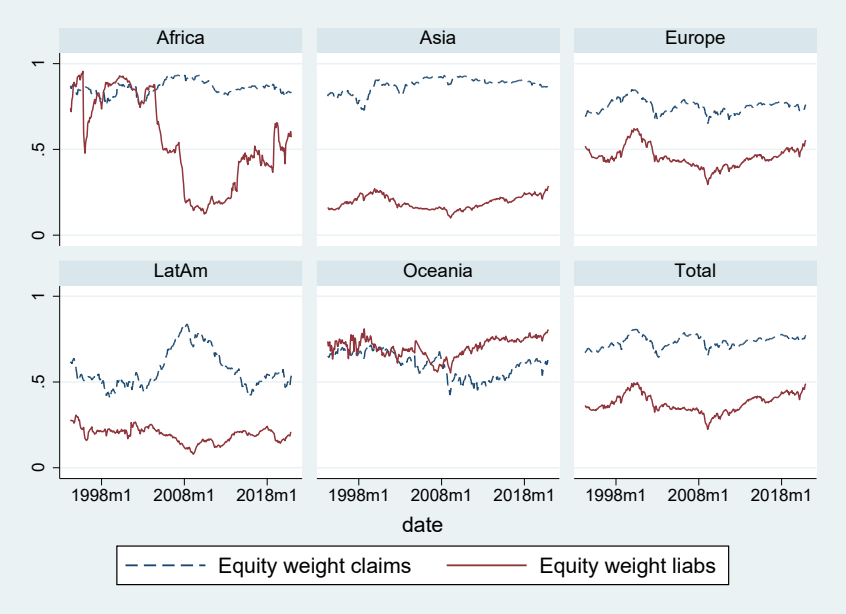
To shed further light on the determinants of the returns we will now progressively decompose the returns by type of assets, by frequency, namely long run versus short run, and by geography.

The Role of Asset Composition. Differences in the dynamics of the cross-border portfolio returns across countries can be due either to differences in individual asset returns or in the composition of the portfolio. We assess the role of the composition by examining in combination the evolution of the portfolio shares of U.S. claims and liabilities vis-a-vis large macro regions and the dynamics of returns for claims and liabilities by asset class.

Figure 2 shows the dynamic of the share of equity in the portfolio for U.S. claims and liabilities[18]. Their counterpart is the share of bonds. First, equity shares in U.S. claims are much higher than equity shares in U.S. liabilities for most regions, hence bond shares in U.S. claims are lower. Specifically the equity share in U.S. claims ranges from 70% to 80%, with an average over the sample period 1995-2020 of 75%. Given this, and since equities grant a premium over other asset classes, differences in the value-weighted returns between claims and liabilities is largely due to differences in the portfolio composition. A second fact is that the shares are remarkably stable over time (with the exception of Africa), hence portfolios are sticky. This is in line with classical mean-variance portfolio optimization. There is also increasing evidence of passive investors bench-marking indexes (see Haddad et al. (2021)). The tendency of American investors to invest in equities is also linked to their preferences and risk-attitudes, and those tend to remain invariant.

18 For this part of the analysis we employ the classical Treasuries International Capital Statistics available at: https://home.treasury.gov/data/treasury-international-capital-tic-system. Some more details are given in appendix A.

Figure 2: **Equity share of portfolio investment in claims and liabilities by region.**

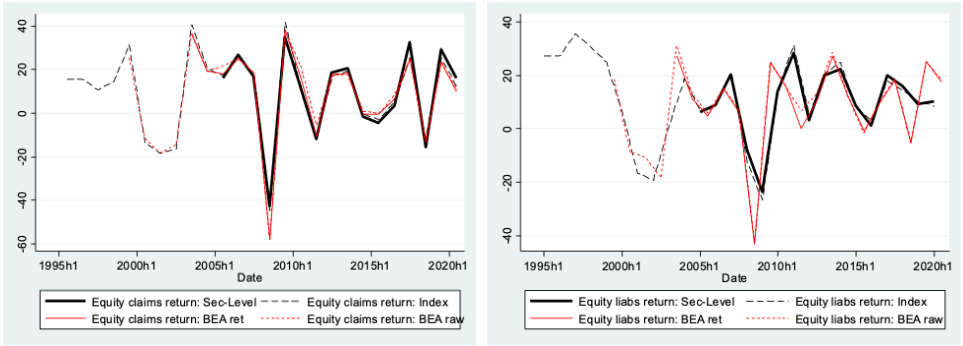


Next, we examine the portfolio returns by asset class. First, Table 2 and 3 presents averages of portfolio returns over the sample period 2005-2020 and across methods, broken down per asset classes and across claims and liabilities (Table 9 in Appendix C shows the same comparison, but for the unbalanced panel and Table 10 in the same appendix shows the returns computed across the four methodologies.). Table 2 also breaks down the returns across sub-periods. Several considerations emerge. First, the returns on equities are consistently higher than bonds in all methods due to the equity premium across all methods and all sample periods. As a proxy of the excess return we take the average return differential between equity claims and bond liabilities which, over the period 2005-2020, is 5.27 in the security method and 4.50 in the BEA-method. In both cases it is close to the classical equity premium. This observation coupled with the fact that we observe a steady share of equities in the U.S. claims at around 80% makes us conclude that the overall excess return between claims and liabilities is largely due to the composition of U.S. claims which is tilted toward equities. Second, some decline in the U.S. return differential between claims and liabilities in the sample 2010-2015 (table 11 in Appendix C presents an alternative time sample cut for robustness reasons. The picture is pretty similar). This is due to two reasons. The first a rebound of the value of U.S. equities in the aftermath of the 2007 crisis: increase in U.S. equity valuation is transferred to the rest of the world at least for the share of equity

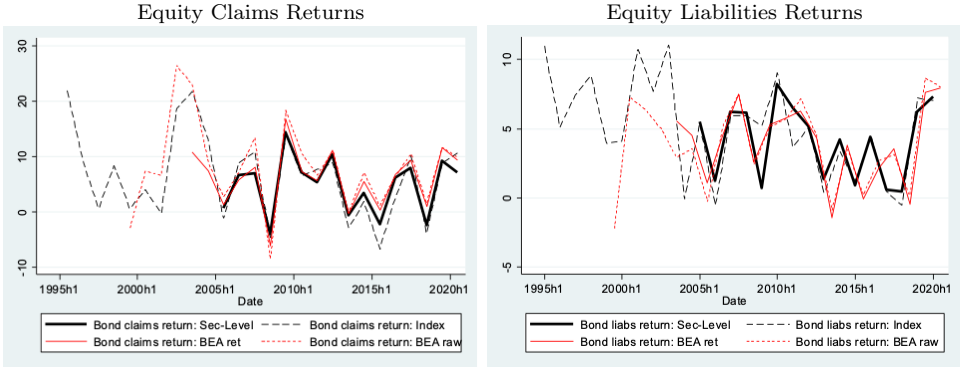
liabilities. Second the sample period in which we observe negative excess returns coincides with the sovereign bond crisis in Europe: the idea that in period of global distress investment in safe U.S. bonds provides an insurance to the rest of the world is compatible with the idea of the exorbitant duty (see Gourinchas and Rey (2022)).

At last, the equity returns on claims and liabilities are remarkably similar, as one would expect given that broadly diversified portfolios are arbitraged across countries on average. For bonds, returns are in the same ball park for both claims and liabilities, albeit smaller for the latter, suggesting that the U.S. bonds retain some convenience yield. The geographical decomposition, presented further below, will allow us to shed further light on the convenience yield. Overall however we can safely conclude that a large part of the exorbitant privilege in U.S. portfolio returns is likely linked to the composition of U.S. claims, which is tilted toward equities.

Figure 3: **Dynamic of equity and bond returns for claims (left panel) and liabilities (right panel). See Table 1 for definitions.**



Equity Claims Returns | Equity Liabilities Returns



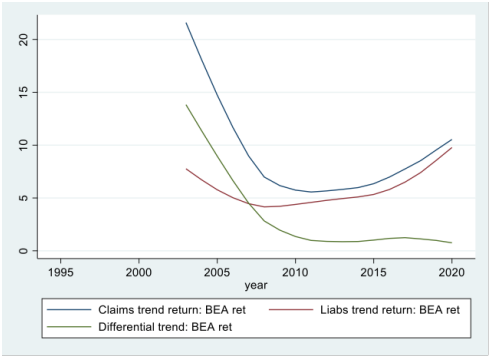
Bond Claims Returns | Bond Liabilities Returns

To complete our comparative assessment figure 3 plots the dynamic of returns for claims (left panel) and liabilities (right panel) using the security-level data, broken down by asset class and showing estimates for each method. Once again the dynamic of the returns is broadly the same across methods, but significant differences with respect to the security-level calculations are visible for liabilities in the later sample. The other aspect of interest is the ranking of returns per asset class between claims and liabilities. As expected the plots reveal that equity returns are higher than bonds, for both claims and liabilities, and this is due to the equity premium. The patterns are also broadly similar.

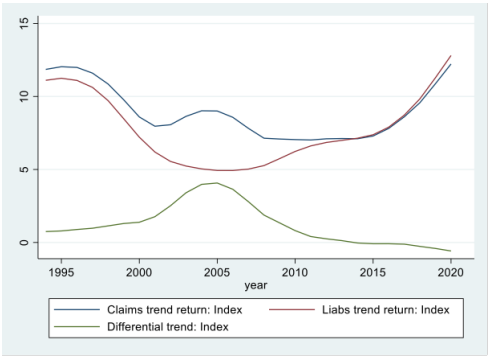
Trends in Claim and Liability Returns and Differentials. The dynamic plots shown so far capture portfolio variation over time and also the salience of some events, such as the financial crisis. Securities data are however highly volatile, while the notion of the return differential as capturing wealth transfer applies to the long run. Therefore we now compute trends which inform on the long run dynamic of the wealth allocation across countries. For robustness we de-trend the returns using two alternative methods, the Hodrick Prescott (HP) filter and the Hamilton filter (Hamilton (2018)), which is less sensitive to starting date. A comprehensive comparison across all the methods considered for computing trends and for measuring returns is presented in Appendix C.1, which discusses also the relative advantages of each method.

Figure 4 shows the HP trend for claims and liabilities and across the three methodologies for computing returns, namely BEA, index and security-based. The figure is complemented by the average trend returns computed over the balanced sample period 2005-2020 and shown in Table 4 for claims, liabilities and their differentials. First, the differences in the long run dynamic across methods is once again more evident for the liabilities. All returns of each asset type, of both claims and liabilities and their differential, trend up in the most recent period. This is more pronounced when we employ the security based method. As known the dynamic of the trends is partly also affected by the underlying business cycle volatility, so that periods of mild volatility shift the trends upward.

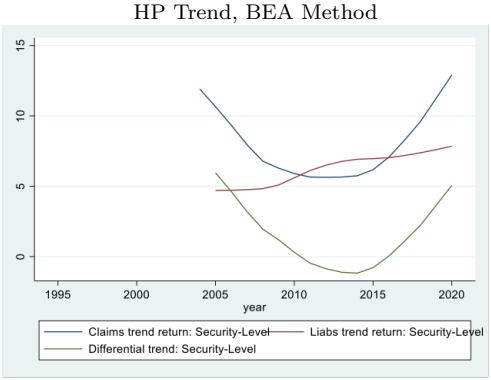
Figure 4: Trend returns for claims, liabilities and differentials across methods: BEA, Index and Security. Data de-trended with Hodrick-Prescott filter with a smoothing parameter of 6.25. See Table 1 for definitions.



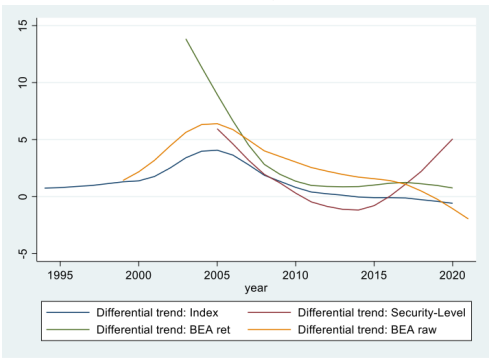
HP Trend, BEA Method



HP Trend, Index



HP Trend, Security



HP Trend Across Methods

The modern TIC survey, which is conducted annually and contains information for returns and asset characteristics, starts in 2003. So far we have focused on this time sample. We however extend the equity returns backward to 1995 by relying on the less frequent surveys conducted prior to 2003.[19] We do so for two reasons. First, when matching equity shares with firm measures a longer time sample is better suited to study questions related to the allocative role of capital flows. Second, we take the opportunity of the longer time sample also to do further checks on the comparison across de-trending methods. We report a comparison of the equity portfolio returns across three de-trending methods (moving averages, HP and Hamilton filters) for the time sample 1995-2020 in Appendix C.2. As before we see no significant differences of the equity returns between claims and liabilities.

19 Specifically surveys took place in 1997 and 2001 on foreign firms and in 1994, 2000 and 2002 for U.S. firms.

Nationality versus Residence. The securities in the TIC surveys are recorded based on the residence of the issuer. Recent work by Bertaut et al. (2019) transforms the data based on the nationality of the reporting issuer.

Examining the returns based on firm nationality is even of greater relevance given our ultimate goal of matching with issuer characteristics and given the increasing trend of firm incorporation in tax havens and/or financial centers. Note that only the security data allow us to apply a nationality correction, while the other methods to compute the returns cannot. We explain in detail the methodology used to compute the nationality correction in Appendix A.3. In brief, the procedure relies on security-level identifiers and text-matching techniques to map each security to the country of exposure for each firm as assigned by commercial products designed for international investors, thus converting these holdings to a "nationality" basis. Information on constituents is obtained from Morgan Stanley Capital International (MSCI) country-focused equity indexes. If a stock is not present in the index the assignment is done manually. For instance, U.S. holdings of Chinese firms such as Alibaba, Tencent, and Baidu (incorporated in the Cayman Islands) are assigned to China for years prior to 2015, although these firms were not included in the MSCI China/Emerging Markets indexes until 2015.

Tables 5 present average returns across time sample and for securities based on nationality. Comparing the results in Table 5 with those presented earlier in Table 2 shows that on the averages there is no differences between residence and nationality. The role of financial centers becomes relevant when we examine the dynamic of the return differential across world regions, something which we do later.

Equity Valuation from BEA to TIC. A final comparison we make between the BEA and the TIC data relates to the equity valuation. Let us remind that BEA receives raw data from the TIC team at the Federal Reserve Board on aggregate equity and other asset shares: so the raw data are the same. The data are delivered in July and BEA publishes the asset positions as well as some estimates of the valuation in December with some timing and capitalization imputations, mostly based on indexes, and adding other components. Details are provided in Appendix A.1.

We compute the capital gains or equity valuation from the securities exactly. Specifically for each security ISIN we download the price from Refinitiv, compute the percentage change and weight it by the respective equity share in the official TIC reporting. The exact formula of the security level capital gains (but they may also be shown over time):

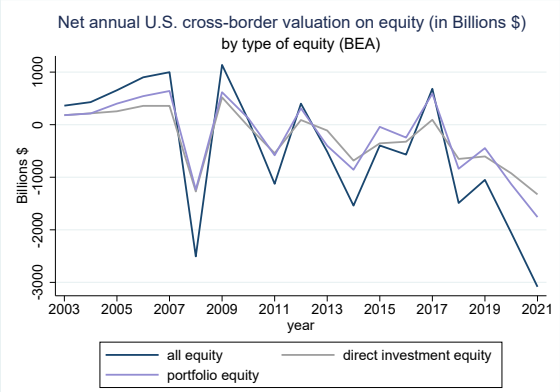
$$V_e = \sum_{j=1}^{N} w_{j,t-1}^{e} \frac{\Delta q_{j,t}}{q_{j,t}} \tag{2}$$

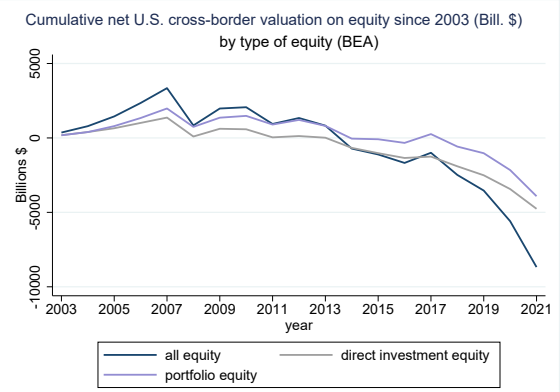
The valuation estimates done by BEA (in dollars) from the IIP include both differences in the price return earned on claims versus liabilities, and the "stock" that the return is applied to. Note that the stock part is the one that most likely may produce difference between the actual data, namely the administrative securities, and the BEA imputations.

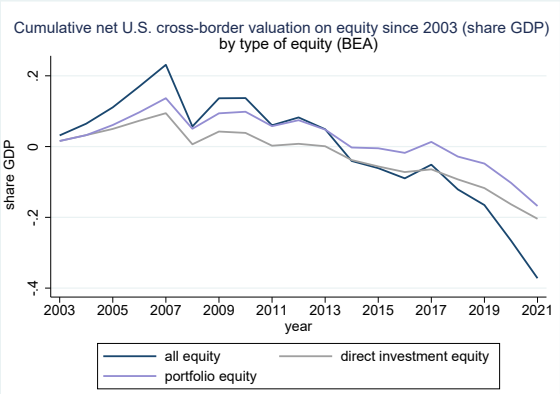
Figure 5 reports the BEA equity valuation annual, cumulative and as percentage of GDP, as well as the comparison with our exact valuation calculations using TIC (last three panels). BEA reports also the valuation of the foreign direct investment, which is not part of the portfolio data, but has occasionally been included in past studies of the U.S. net returns on foreign investment (see recently for instance Atkeson et al. (2022)). The portfolio (lila) and FDI equity valuation (grey) estimates track each other quite closely and each make up about half of the total net equity valuation in any year (blue).

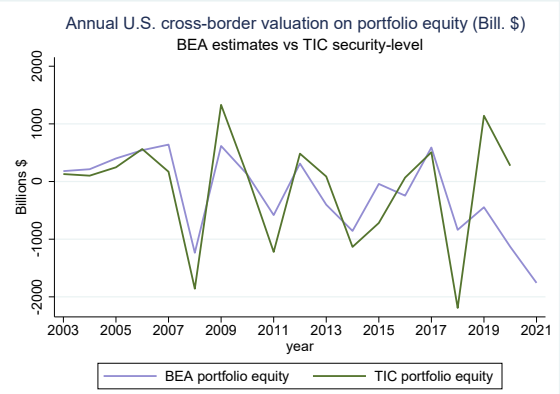
The difference between BEA and our exact valuation with TIC is explained by both the differences in price returns for claims versus liabilities and the differences in the size of holdings of claims versus liabilities. Despite the differences both the BEA and our TIC equity valuations exhibit a downward trend, starting in 2011, and this is most plausibly attributable to the fact that the U.S. stock market outperformed the foreign ones. In the security level valuation the downward trend is much less pronounced and shows a reversal, confirming the temporary nature of some of those valuation changes.

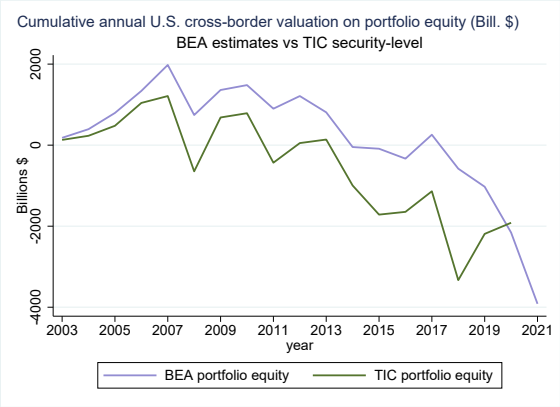
Figure 5: Comparison of BEA and TIC equity valuation. First panel plots annual net equity valuations, i.e. valuation on foreign equity claims minus val. on domestic equity liabilities. Second and third panels present the cumulative net valuation from portfolio positions and foreign direct investment from BEA annual net equity valuations, also as share of GDP (third panel). The last three panels compare the cumulative valuations from BEA data with the one obtained from TIC, also as percentage of GDP (last panel))

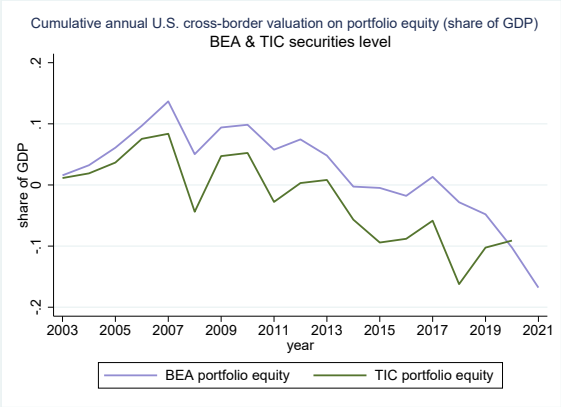












The Geography of the Returns, Nationality and Residence Based. A step forward to understand the origin of the global wealth allocation is to map the geography of the returns for all asset classes and to disentangle where the U.S. earns, or else pays, returns. This is also an intermediate step before examining the firm level relations. To this purpose we compute the average and the dynamic of returns across asset classes and regions, which we group in: Emerging Market Economies, Asia, Europe Core and Europe Others, other advanced,

U.K. and Channel Islands.[20] The groups have been chosen to strike the best balance between providing the right representation of broad geographical regions and avoiding groups of small countries whose returns appear too volatile to reach meaningful economic conclusions.

For the regional decomposition the distinction between residence and nationality is crucial as financial center incorporation is more prevalent in some regions than others. To see this Table 13 in Appendix C.3 reports the magnitude of the securities reassignment in millions of dollars for both equities and bonds and for the 2020. The golden share of the reassignment is taken by the U.S. and China.

We start by examining in which regions U.S. investors earn most of their returns. Table 6 shows that most of the equity returns are earned in Asia, more so under the nationality base. In light of the number of Chinese firms incorporated in financial centers this is understandable. Over the period 2005-2020 U.S. investors earns 12% on Asian equities, around 9% on European equities, against the 9% earned by foreign investors on U.S. firms.

Next we examine the returns on claims per asset class, over the period 2004-2020, with liability returns across the regions defined above. Here we focus on equities. Figures 9 compare the dynamic of the equity portfolio return on foreign firms (claims) by region to that of U.S. firms (liabilities), both by nationality (top six panels) and by residence (next six panels). Figure 7 plots, for residence and nationality, the differential between the portfolio return on U.S. equity claims minus that on U.S. Treasuries, capturing a strict notion of excess returns. Trends are similar, although returns on emerging markets are more volatile. No region appears to consistently outperform the others, albeit in the more recent years Asian firms pay higher returns. Indeed most of the differential earned by U.S. investors (figure 7) is earned on Asia. The last panel of figure 9 plots the returns of firms resident in tax

20 Emerging markets include: all countries in Latin America and the Caribbean, all countries in Africa, European EMEs, namely Albania, Armenia, Azerbaijan, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Lativia, Lithuania, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Turkey, Turkmenistan, Ukraine, Uzbekistan, all other countries, i.e. Marshall Islands, Papua New Guinea, Samoa and International regional organizations, primarily IMF IBRD. Asia includes all countries in Asia excl Japan, and all countries in the Middle East. Europe core includes Austria, Belgium, France, Germany, Netherlands. Europe others includes Andorra, Cyprus, Denmark, Finland, Gibralter, Greece, Greenland, Iceland, Ireland, Italy, Lichtenstein, Luxembourg, Malta, Norway, Portugal, San Marino, Spain, Sweden, Switzerland, Vatican City. Other advanced includes Canada, Japan, Australia, New Zealand.

havens but national somewhere else: their size confirms that a significant part of U.S. equity investment is channelled through the Caribbean centers.

Appendix C.4 plots the regional decomposition for the dynamic of returns for other asset classes. It is worth mentioning that the U.S. convenience yield is still visible, but primarily vis-a-vis countries with high sovereign risk. On average over the usual sample period U.S. Treasuries pay a return of 3.7% against a 6.2% for Asian ones and a 3.9% for European ones. For total corporate bond returns the difference is less marked. U.S. bonds pay on average 4.4%, Asian 5.5% and European 5.4%.

Figure 7: **Excess Return by Region. Returns on equity computed using location based on either firm nationality (top two panels) or residence (top bottom panels) minus returns on U.S. Treasuries (left panel) and U.S. agencies (right panel) in 2004-2020.**

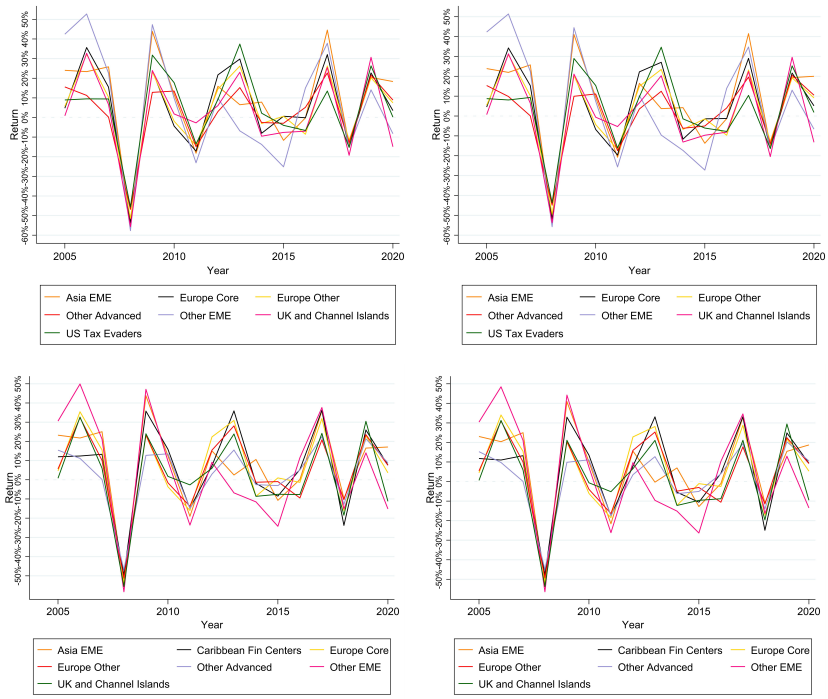
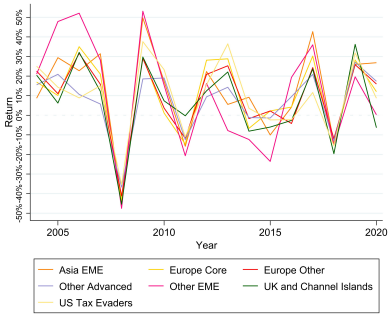
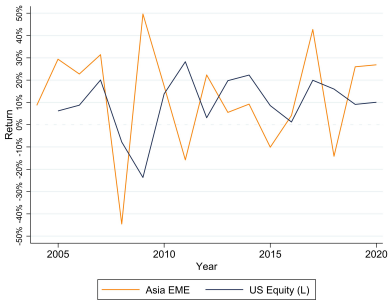


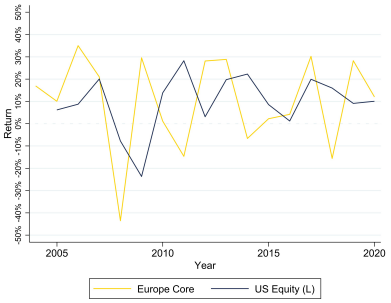
Figure 9: **The figure compares the returns, computed using the security-based method, on US claims to foreign equities across the following regions Asia, Core Europe, Emerging Markets, U.K. and Caribbean and financial centers. Returns are compared to returns earned by foreign on equities by U.S. firms. The top six panels shows the returns when securities are assigned based to countries based on firm nationality; the next six plot returns for securities on residence base. The time period is 2004-2020. Country list in geographical regions is defined in the main text.**



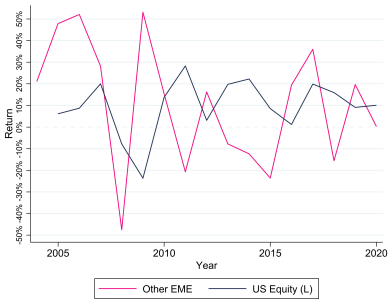
All Foreign and US



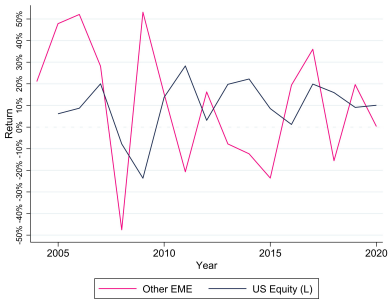
Asia vs US



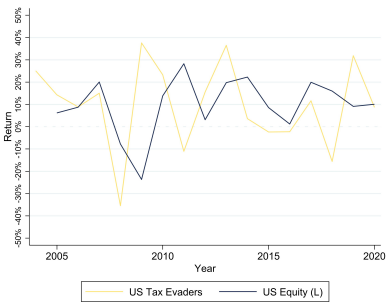
Core Europe vs US



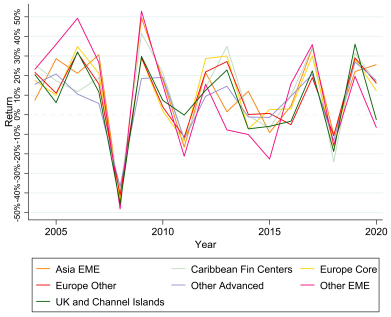
Emerging Economies vs US



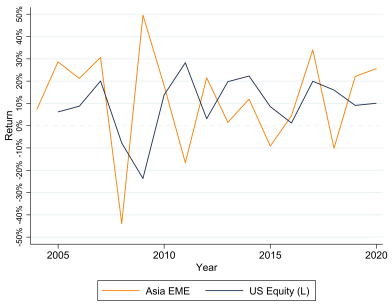
UK, Channel Islands vs US



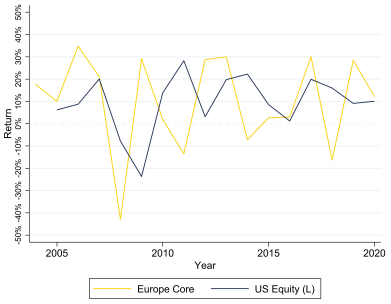
US Non-resident vs US



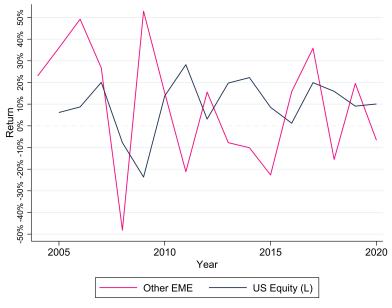
All Foreign and US



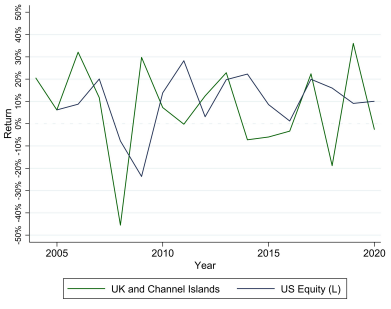
Asia vs US



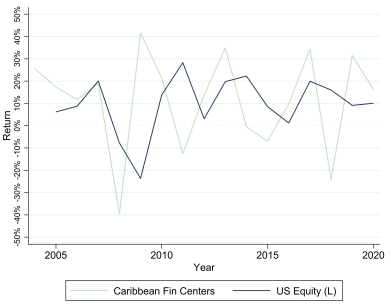
Core Europe vs US



Emerging Economies vs US



UK, Channel Islands vs US



Caribbean Fin Centers vs US

Table 2: **Average returns and differentials by asset type from 2005-2020. Residence Basis. See Table 1 for definitions.**

Security-Level	2005-2009	2010-2014	2015-2020	Total
Equity return claims	10.27	7.39	10.13	9.32
Equity return liabilities	0.69	17.44	10.80	9.71
Bond return claims	4.89	5.03	4.26	4.70
Bond return liabilities	3.94	5.07	3.29	4.05
Total return claims	8.59	6.56	8.63	7.97
Total return liabilities	2.96	9.06	6.29	6.11
Total return differential	5.23	-1.93	1.97	1.77
Index	**2005-2009**	**2010-2014**	**2015-2020**	**Total**
Equity return claims	11.66	7.22	8.76	9.18
Equity return liabilities	-0.47	19.30	10.33	9.76
Bond return claims	5.62	4.42	3.60	4.49
Bond return liabilities	4.37	4.29	3.29	3.94
Total return claims	9.69	6.29	7.43	7.78
Total return liabilities	2.90	9.14	6.10	6.05
Total return differential	6.35	-2.19	1.01	1.68
BEA	**2005-2009**	**2010-2014**	**2015-2020**	**Total**
Equity return claims	8.42	7.96	8.43	8.28
Equity return liabilities	1.47	13.26	10.73	8.63
Bond return claims	5.16	5.82	6.40	5.83
Bond return liabilities	4.22	3.74	3.45	3.78
Total return claims	7.62	7.35	7.93	7.65
Total return liabilities	3.44	7.25	6.60	5.82
Total return differential	4.18	0.09	1.33	1.83

Table 3: **Average returns by asset type, 2005-2020. See Table 1 for definitions.**

By residence	Security-Level	Index	BEA ret	BEA raw
Equity return claims	9.32	9.18	8.28	9.53
Equity return liabilities	9.71	9.76	8.63	9.49
Bond return claims	4.70	4.49	5.83	6.84
Bond return liabilities	4.05	3.94	3.78	3.93

Table 4: **De-trended returns for claims, liabilities and differentials, computed across four methods. Two different trending methods: Hodrick-Prescott with smoothing parameter based on Ravn and Uhlig (2002) and Hamilton (2018) method. Balanced panel 2005-2020. See Table 1 for definitions.**

	Security-Level	Index	BEA ret	BEA raw
Claims return HP	7.99	8.04	7.61	8.93
Liabilities return HP	6.12	6.03	5.92	6.36
Differential HP	1.78	1.91	1.69	2.57
Claims return Hamilton	5.84	7.52	7.07	9.37
Liabilities return Hamilton	5.90	5.92	5.82	5.95
Differential return Hamilton	-0.08	1.55	1.25	3.41

Table 5: **Average returns and differentials by asset type from 2005-2020. Nationality Basis. See Table 1 for definitions.**

Security-Level	2005-2009	2010-2014	2015-2020	Total
Equity return claims	10.37	7.39	8.72	8.83
Equity return liabilities	0.69	17.44	10.94	9.69
Bond return claims	4.94	5.10	3.76	4.60
Bond return liabilities	3.79	5.22	2.52	3.84
Total return claims	8.67	6.59	7.43	7.57
Total return liabilities	2.82	9.41	6.06	6.10
Total return differential	5.84	-2.81	1.38	1.47

Table 6: **Security based portfolio equity returns by region for all foreign firms and for U.S. firms. Average for the years 2005-2020.**

Regions of Firm by Residence	Average Equity Returns	Region of Firm by Nationality	Average Equ
United States	0.08	United States	0.09
Other EME	0.02	Other EME	0.11
Asia EME	0.12	Asia EME	0.11
Core Europe	0.10	Core Europe	0.09
Europe Other	0.09	Europe Other	0.09
Other Advanced	0.09	Other Advanced	0.09
U.K.	0.04	U.K.	0.07
Total	0.08	Total	0.069

3. The Role of Capital Flows for Allocative Efficiency

Our next step is to leverage on the disaggregated nature of our data and to match them with firm characteristics, capturing production, market and financial structure. We are interested in particular in the role that capital flows may have for allocative efficiency. We assess this by examining how capital allocates along the distribution of firm MPK and other allocative market and financial wedges. We examine how equity shares are allocated over the entire sample period starting in 1995 and also track how the reallocation along the distribution of firm characteristics changed over time.

The expanding literature on capital mis-allocation has uncovered two main paths. On the one side (see Hsieh and Klenow (2009) among others) it has linked mis-allocation to larger dispersion of capital and funding sources across firms (for the latter see Bau and Matray (2023)). On the other several papers have uncovered patterns of reallocation to the top (see Autor et al. (2020) or Baqaee and Farhi (2020b)). In the latter case firms dispersion still signals mis-allocation of resources, however the reallocation to the top, following shocks from increased competition to expanding markets, may reduce the distance from the pareto frontier. Firms with larger wedges have lower allocation of resources than under the efficient equilibrium, as such the reallocation to the top shrinks the distance to the pareto frontier, albeit never reaching it. Focusing on oligopolistic wedges such a phenomenon is more likely to emerge under non-homothetic preferences for a variety of aggregators. Those preferences imply lower elasticities of demand for firms at the top of the distribution. Those firms can then charge higher mark-ups and hence end up producing less than under the efficient allocation. While this literature is primarily concerned with the allocation of inputs and its consequences for aggregate productivity, it does have implications for the allocation of funding. As firms at the top of the wedge distribution are smaller than they should be, they also command a larger allocation of funding to get closer to the frontier. A paper that examines the allocative role of equity funding is Bau and Matray (2023) that documents indeed a decline in mis-allocation following the opening of equity funding of India from abroad. Apart from their study, the implications of mis-allocation for the allocation of international capital flows has so far largely remained unexplored. This indeed requires the exact links

between firms measures that may proxy mis-allocation and international securities, a link that our study provides. The main arguments are carried out by examining the allocation of individual equity shares along the distribution of MPK and market and financial wedges.

To carry forward the plan above the first step is the estimation of firm measures related to production, market and financial structure, which we present next. From now we will focus on data based on firm constituency by nationality, as the goal is to correctly assign the returns to the ultimate issuer.

3.1. Measuring Firm MPK, Productivity and Wedges.

The first measure we consider is the firm marginal productivity of capital (MPK in short), which under a classical Cobb-Douglas production function, can be obtained from the ratio of revenues over the cost of capital. This measure has several advantages. Dispersion in MPK signals dispersion in wedges, hence misallocation. Another advantage of this measure is that contrary to other productivity and market measures, described next, it does not require a production function estimation which typically tends to impose restrictive assumptions and hence forces us to drop many firms whose data do not comply with the requirements.

Firm productivity is measured from the estimated production elasticitiy following Olley and Pakes (1996) or Levinsohn and Petrin (2003). Measures of market power are obtained through the production or proxy method (De Loecker and Warzynski (2012), De Loecker and Eeckhout (2018), Baqaee and Farhi (2020b), Doraszelski and Jaumandreu (2019)), which identifies wedges by merging firm first order conditions from cost minmization on labour and other variable inputs. Following this procedure the mark-up reads as the ratio between the output elasticities and the cost share of variable inputs. The output elasticity is estimated is obtained once again through production function estimation (see Olley and Pakes (1996) or Levinsohn and Petrin (2003)), while the cost shares are obtained from firm accounting databases. The advantage of the method is that it takes an agnostic perspective on the type of market structure or oligopolistic competition, and as such it may also capture wedges stemming from variable elasticity of demand or other nominal frictions. The analytical background behind those measures is presented below.

For the firm accounting databases we use both Global Compustat and Worldscope. The first provides our benchmark as its matching with the TIC data is the best. More likely this is so since Compustat includes large and listed firms, whose securities are more likely to be traded internationally. For robustness reasons we estimate all measures also in Worldscope and check the consistency of our main regression across the two databases.[21]

Model Structure for Firm Productivity and Market Measures. Our measure are derived using the cost minimization or production approach. First our baseline measure, namely firm marginal product of capital, is obtained from firm first order condition for capital. Under a standard Cobb-Douglas production function firm marginal productivity of capital can be recovered as the ratio of revenues over capital input costs (see also Bau and Matray (2023)). Next, we derive the firms' cost minimization problem that serves as basis for both productivity and market wedge measures.

Firm j produces output Q_{jt} ij period t with any given amount of capital, K_{jt}, and freely variable amounts of labour and materials, L_{jt} and M_{jt}, with production function:

$$Q_{jt} = Q^*_{jt} exp(\epsilon_{jt}) = F(K_{jt}, exp(\omega_{Ljt} L_{jt}, M_{jt}) exp(\omega_{Hjt} + \epsilon_{jt}) \tag{3}$$

where ω_{Ljt} is a labour 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. Capital is taken as given due to adjustment costs. As for the variable input 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 unexpected to the firm at the time of choosing the inputs. Let us define $VC_{jt} = W_{jt} L_{jt} + P_{Mjt} M_{jt}$ as the variable cost, firms' costs minimization problem reads as follows:

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

21 Compustat has roughly 30,000 firms and Worldscope includes others rounding up to 70,000. The securities in the TIC are issued mainly by large and global firms, which are better represented in Compustat. The matching between the TIC securities and Compustat reaches 87% on average across periods for U.S. firms, while the matching with Worldscope is somewhat lower, namely 73% average across all years for U.S. firms and 68% for foreign firms.

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

$$W_{jt} = \lambda_{jt} \frac{\delta F(K_{jt}, exp(\omega_{Ljt}) L_{jt}, M_{jt}) exp(\omega_{Ljt} + \omega_{Hjt})}{\delta L_{jt}} \tag{4}$$

and

$$P_{Mjt} = \lambda_{jt} \frac{\delta F(K_{jt}, exp(\omega_{Ljt}) L_{jt}, M_{jt}) exp(\omega_{Hjt})}{\delta M_{jt}} \tag{5}$$

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

$$M_{jt} = M(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt}) P_{Mjt}}), \frac{Q^*_{jt}}{exp(\omega_{Hjt})} \tag{6}$$

and

$$L_{jt} = L(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt}) P_{Mjt}}), \frac{Q^*_{jt}}{exp(\omega_{Hjt})} exp(\omega_{Ljt}) \tag{7}$$

Substituting these demand into the variable costs one obtains:

$$VC_{jt} = VC(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*}{)} exp(\omega_{Hjt}) \tag{8}$$

Hence the marginal cost is:

$$MC_{jt} = \frac{\delta VC_{jt}}{\delta Q_{jt}} = VC(K_{jt}, \frac{W_{jt}}{exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*}{exp(\omega_{Hjt})}) \tag{9}$$

Since $\lambda_{jt} = MC_{jt} = \frac{\delta VC_{jt}}{\delta Q_{jt}}$ as per envelope theorem, we can re-write equations 4 and 5 as: $\frac{1}{MC_{jt}} = \frac{\frac{\delta Q_{jt}}{\delta X_{jt}}}{W_{Xjt}}$, where $X_{jt} = L_{jt}, M_{jt}, W_{Xjt} = W_{jt}, P_{Mjt}$ and MC_{jt} is the marginal cost based on planned output and the conditions for the marginal productivity of every marginal dollar must be the same in every use. By multiplying on both sides of equation 9 by the average marginal costs at planned output, one obtains AVC:$\frac{AVC_{jt}}{MC_{jt}} = \frac{\frac{X_{jt}\delta Q_{jt}}{Q^*_{jt}\delta X_{jt}}}{\frac{X_{jt}W_{Xjt}}{VC_{jt}}}$. Finally, by defining

$\beta_{Xjt} = \frac{X_{jt}\delta Q_{jt}}{Q^*_{jt}\delta X_{jt}}$ as the elasticity of production to each input X_{jt} and $S_{Xjt} = \frac{W_{Xjt}X_{jt}}{P_{jt}Q^*_{jt}}$ as the share of input bill in variable cost we can rewrite the first order condition as follows:

$$\nu_{jt} = \frac{\beta_{jt}}{S_{Xjt}} \tag{10}$$

and where we have set $\frac{AVC_{jt}}{MC_{jt}} = \frac{1}{\nu_{jt}}$, namely the inverse of the elasticity of the variable cost with respect to output.

The estimation of elasticities follows Olley and Pakes (1996). The procedure consists in two steps. In the first step one estimates the disturbance that separates observed output from relevant output. Olley and Pakes (1996) start by assuming that $\omega_H = h(x_t)$ where x_t is a vector of observables and x_{jt} collects all arguments of the production function, such as input prices and demand. Olley and Pakes (1996) use the demand for investment to invert for productivity, while Levinsohn and Petrin (2003) use the demand for a variable input. In either case production is loglinearized and expressed as follows:

$$q_{jt} = ln(F(K_{jt}L_{jt}, M_{jt})) + h(x_{jt}) + \epsilon_{jt} = (x_{jt}) + \epsilon_{jt} \tag{11}$$

where (x_{jt}) is a flexible functional form that must be estimated non parametrically and assuming that the error term is orthogonal. Estimates of and ϵ separate planned from actual output. In the second step the elasticities are estimated in the regression:

$$q_{jt} = lnF(K_{jt}, L_{jt}, M_{jt}) + g_t(_{jt-1} - ln(F(K_{jt-1}, L_{jt-1}, M_{jt-1})) +_{jt} +\epsilon_{jt} \tag{12}$$

where the latter specification is valid under the assumption of Markovian productivity and the conditional expectation function g is also estimated non-parametrically.

To obtain the mark-up it suffices to note that this is $\mu_{jt} = \frac{P_{jt}}{MC_{jt}}$ and to multiply 10 by $\frac{P_{jt}}{AVC_{jt}}$ to get:

$$\mu_{jt} = \frac{\beta_{Xjt}}{S^*_{Xjt}} \tag{13}$$

where $S^*_{Xjt} = \frac{W_{Xjt}X_{jt}}{P_{jt}Q^*_{jt}}$ is the share of revenues of the amount spent on any given input. The mark-up can also be re-written as:

$$\frac{P_{jt}Q^*_{jt}}{W_{Xjt}X_{jt}} = \frac{\beta_{X_{jt}}}{\mu_{Xjt}} exp(\epsilon_{jt}) \tag{14}$$

and the above is actually the expression used for actual estimation. Note that the ϵ is actually an error on the revenues rather than on production.

Threats to identifications and Biases. The size of the wedge crucially depends on correct estimates of the elasticities. The baseline procedure outlined above assumes a Cobb-Douglas production function. Estimates maybe biased if the production is not Cobb-Douglas, but translog or others. To alleviate this we compute elasticities for different production functions.[22] In that case the estimates would produce a range of the elasticities, hence of the wedges.

Extending the Method to Compute Regional Elasticities. Recent work by De Loecker and Eeckhout (2018) also computes mark-ups globally. They use Worldscope data, while our benchmark are Compustat data as their overlap with TIC is superior. The distributions of the firm measures does not differ much between the two: in Appendix C.6.1 we provide a comparison of the mark-up distributions across the two datasets. Beyond that there is another important difference. To compute mark-ups worldwide De Loecker and Eeckhout (2018) use the U.S. elasticities per sector and vary the denominator, namely the cost share of variable inputs. They argue that elasticites 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,

22 We adopt the PRODEST routine by Rovigatti and Mollisi (2020).

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.[23] Further details on the data and computations are reported in appendix B.

Regional Distribution of Firms Measures. Before examining the firm distributions over time in the TIC dataset in Appendix B.2 we report them, across different regions and sample periods, for both Compustat and Worldscope datasets and also comparing different estimation methods. The goal is to document changes in firm distribution and market concentration for firms worldwide and more generally. We examine both changes in the average mark-up (weighted by market shares) and in the distributions. We find that aggregate mark-ups have increased everywhere and not only in the U.S. One of the largest shifts forward in the mark-up distribution is actually observed for Chinese firms.

Firm Distributions in U.S. Claims and Liabilities. Next we match the estimates of the firm wedges to the TIC securities data (see Appendix B for details on the matching procedure), both the equity returns and the portfolio shares. Firm measures computed in the Global Compustat dataset represent our baseline as the matching with TIC is superior. In all cases we repeat matching and estimates with Worldscope for robustness. The first goal is to assess whether similar or larger shifts in the densities of the firm wedges are observable in the portfolio of international securities. If so this would provide a first assessment of the link between firm wedges and capital flows data. When plotting the densities we also interact with a sector dummy: if shifts in the distributions have occurred this interaction inform us about which sectors were involved.

The densities we plot are weighted by firm market capitalization. This has two purposes. Contrary to the perspective taken in the industrial organization literature that uses market shares, the weighting by market capitalization allows us to take into account the market to which rents accrue rather than the market in which rents are generated.

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

Figures 10 and 12 show the kernel densities for the usual time samples of the mark-ups, weighted by market capitalization and broken down by sector, and for the firms represented in the TIC dataset, in both claims and liabilities. In each figure the panels in the upper part present the kernel densities with a view from the top, which allows us to detect shifts in the average, and the panels in the bottom part present the kernel densities with a view from the front, which allows us to detect shifts in the tails.

The frontal kernel densities clearly show that the sectors exhibiting the largest shift forward in the recent sample are retail, BioTech and financial. This is true both for claims, hence foreign firms, and liabilities, hence U.S. firms.

It is of interest also to examine whether those shifts were due to increases in the average or due to shifts in the tail of the distribution. Table 7 shows the growth in market capitalization of each sector and for the securities in the U.S. claims and liabilities, as well as the mean and median market wedge by industry over the two time periods considered so far, namely 2004-2009 and 2014-2019. The most relevant shifts relate to the financial and the BioTech sectors. The first exhibits a shrink in the top tail, most likely due to a reduction in the size of financial firms following the financial crisis, albeit an increase in the average mark-up. The density of firms in BioTech instead shows a fattening of the upper tail, hence a growth in firm size mostly at the top, and almost no change in the average mark-up. Those considerations combined with the observed shifts in the distribution imply that firms in the financial sectors are the one with the largest growth in average mark-ups (the box in figure 10) and the largest decline in the top tail. The opposite is true for BioTech: in this case the shift in the mark-up distribution is mainly due to the growth of market shares for firms at the top tail, or superstars.

What is more interesting is that shifts are more marked for the firms that issue international equities, hence those in TIC relatively to those in Compustat: for instance for the period 2000-2020 the average mark-ups grew from 1.95 to 2.3 for the first and from 1.4 to 1.9 for the second. This already suggests that international portfolios have a stronger allocative role than domestic ones.

Table 14 in appendix C provides the Kolmogorov Smirnov tests for the significance of the

shift across sectors. For U.S. firms, the shift is significant for firms in the financial sector, but results for BioTech are less strong. For foreign firms there is a significant shift in markup distributions for firms in financial, BioTech, manufacturing, and consumer industries. First, we conclude that only some sectors contributed to the rise in the mark-ups. Second, the shift in the U.S. is not larger or more significant than the one observed in other countries.

3.2. Allocation of Shares in External Holdings to the Top.

Given the shifts in the firm distributions documented above, we are now interested in examining their link to capital flows. In particular and in light of the literature on misallocation (see Baqaee and Farhi (2020b)) we are interested first and foremost in assessing whether portfolio shares are consistently and significantly allocated to firms with high marginal productivity of capital and wedges. To assess this link our main econometric specification links the equity portfolio shares, net of market capitalization, at security level to MPK or other firm measures. Formally the regression specification reads as follows:

$$s_{i,t} - \overline{s}_{i,t} = \gamma + \alpha x_{i,t} + \epsilon_{i,t} \tag{15}$$

where $s_{i,t}$ he portfolio share for security i relative to the total holdings of the security, $\overline{s}_{i,t}$ is the market cap of security i, which we obtain from Worldscope, and $x_{i,t}$ is the wedge of firm i. Netting out market cap serves two purposes. First, it allows us to distill the firm component. Second, market capitalization reflects market index shares which per se induce an allocation of shares toward firms with high valuation, hence at the top of the distribution. Our interest lies in establishing whether we observe an allocation of capital flows toward the top of the distribution that is on top and above the one induced by the market index. Further, note that the specification is at firm level. This is a somewhat unconventional perspective with respect to the literature studying the link between capital flows and productivity, which generally adopts country level specifications. First, the firm level measures are more precise, more so for variables such as MPK. Second, firm capitalization per country has low coverage, hence

Figure 10: **Figure 10 plots the kernels densities of market wedges weighted by market capitalization (elasticities computed with Olley and Pakes (1996)) for U.S. firms, estimated with Compustat data and represented in the TIC securities liabilities. Wedges are weighted by market capitalization and the densities are across all firms in the TIC dataset averaged across two sample periods, 2004-2009 and 2014-2019. Each panel reports the name of the industry. The top figure shows the kernel densities from above, while the bottom figure shows them from the front.**

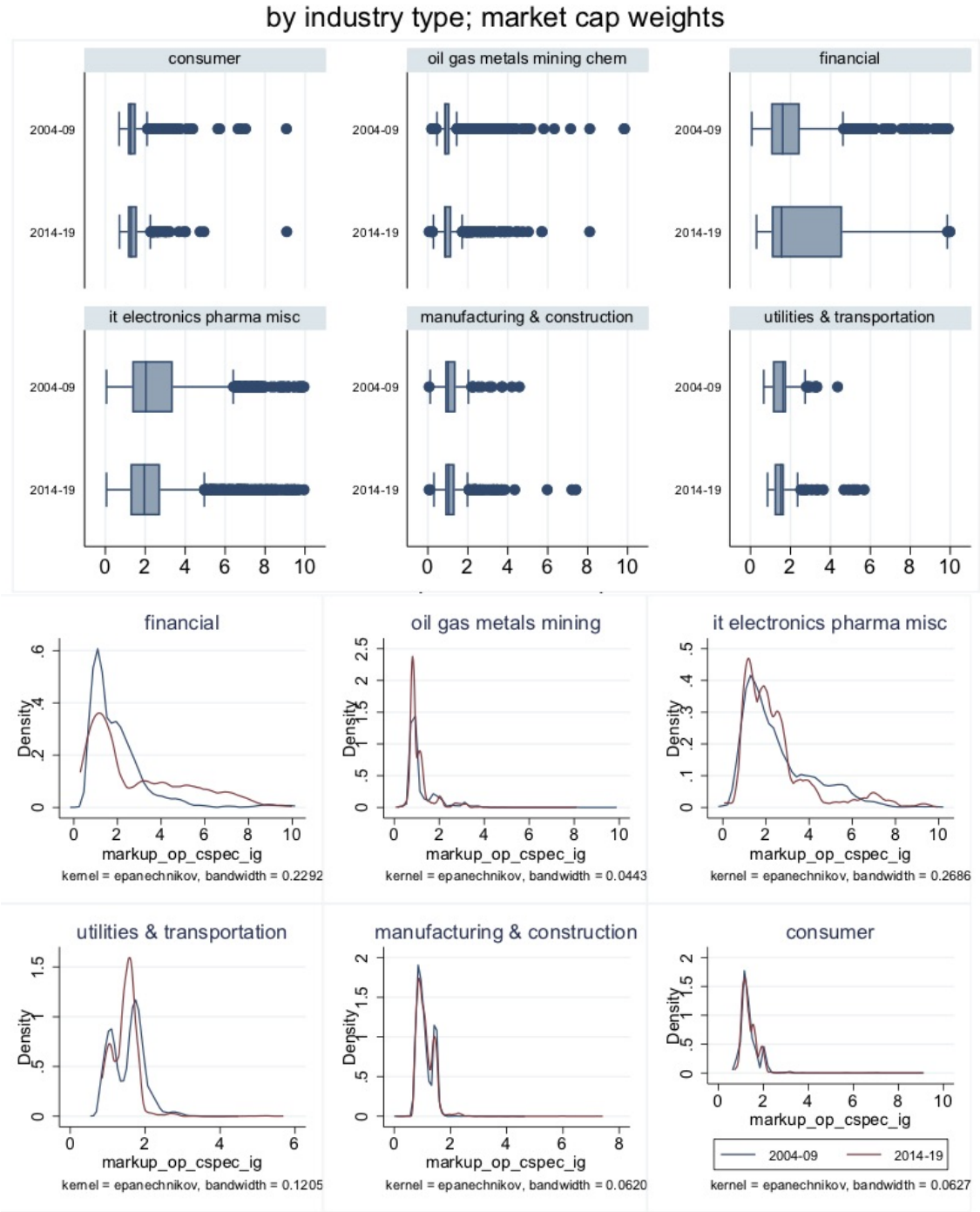
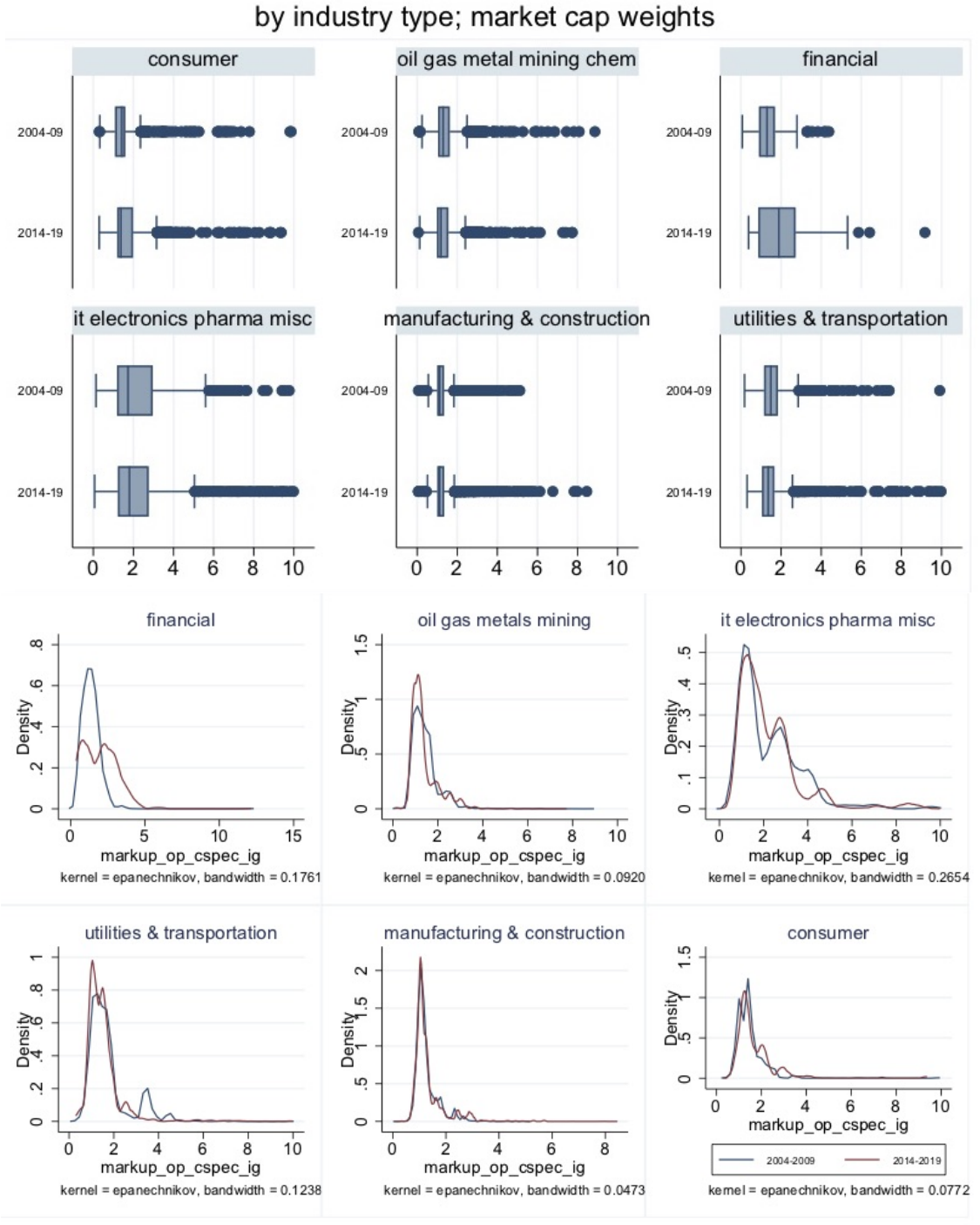


Figure 12: **Figure 12 plots the kernels densities of market wedges (elasticities computed with Olley and Pakes (1996)) for foreign firms, estimated with Compustat and represented in the TIC securities claims. Wedges are weighted by market capitalization and the densities are across all firms in the TIC dataset averaged across two sample periods, 2004-2009 and 2014-2019. Each panel reports the name of the industry. The top figure shows the kernel densities from above, while the bottom figure shows them fro the front.**



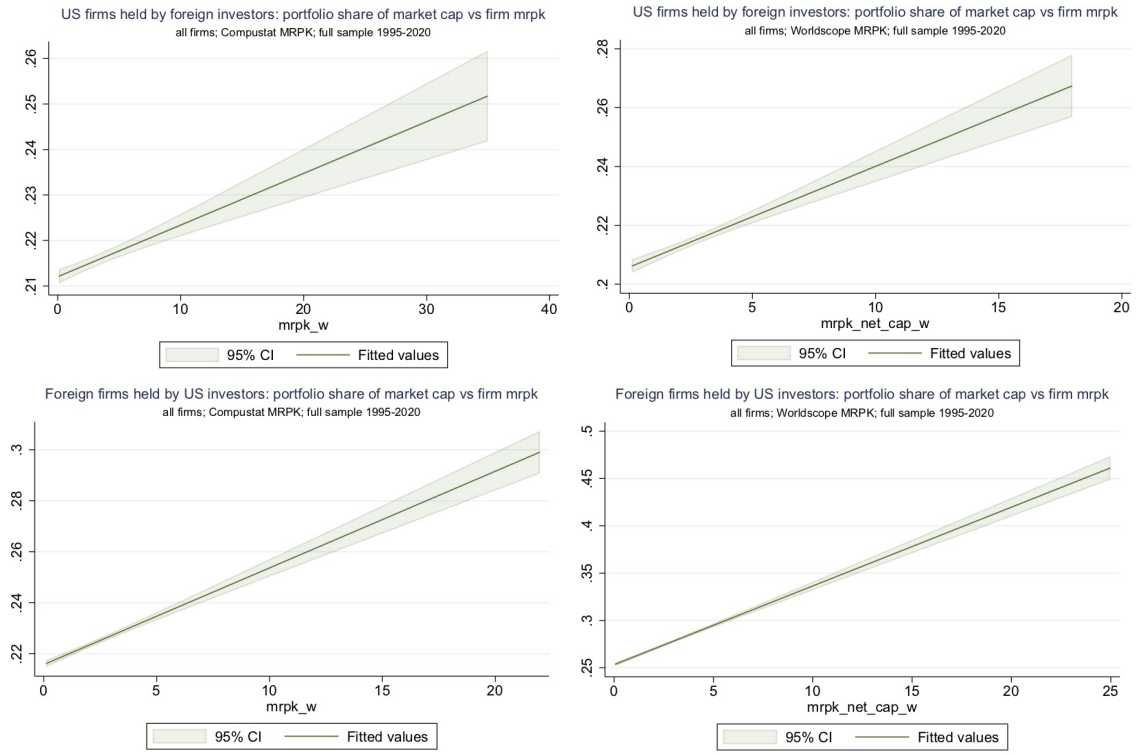
it would not allow us to net out for the effect of the indeces. At last, highly disaggregated specifications provide a closer identification of the channels.

Two other remarks are useful. First, we choose to estimate equation 15 with one firm measure at a time. We could include several measures jointly, but it is likely that some will be correlated with each other. Second, for this tests we focus on data at nationality level as they best represent firm operating location.

We start by examining the regression results for the full sample of U.S. and foreign firms; next we drill down by regions and sectors. The first measure we consider is the marginal productivity of capital (MPK in short). As argued earlier this measures has several advantages. It provides a general sense of allocative efficiency. Moreover since it does not require the production function estimation, which is pretty demanding, it allows us to retain the largest number of firms matched with the TIC securities (see Bau and Matray (2023)). Figure 17 shows that the correlations are positive and significant at 95% confidence interval for both claims (shown in top panels) and liabilities (shown in bottom panels), hence equity securities are allocated toward firms with higher MPK. The left panel of the figure show the correlations with estimates from Compustat and the right panels with those from Worldscope. The estimated coefficient (for the Compustat sample) is significant, with a standard deviation of 0,0002137 and 0,0011364 respectively and a t-stat of 17.74 and 7.16 respectively for claims and liabilities. The economic magnitude are also meaningful. For instance for liabilities, for which the mean equity share is 0.21, a one standard deviation increase in MRPK implies a 3.97266 estimated increase in the portfolio share of the corresponding firm. The allocation to the top is therefore less strong for liabilities, that is for shares of foreign investors to U.S. firms.

This positive correlation, which is present both for U.S. and foreign firms, provides a new rationale for capital as improving allocative efficiency. Further below we show that the same correlation is negative for domestic portfolio shares, hence in a diff and diff design across firms receiving foreign or domestic capital we observe reallocation at the top only for the first. Moreover a break down by sector, shown below, shows that the reallocation to the top is stronger in sectors such as BioTech. Table7 shows that those firms also grow more in terms

Figure 14: **Figure 17 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities and claims in the TIC dataset with the marginal productivity of capital of the issuing firm estimated through Compustat and Worldscope data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.**



of market capitalization. Hence larger availability of funds make those firms bigger, boosting efficiency. In combination those results provide a rationale for an allocative role of capital flows that by providing resources to best performers overcomes domestic misallocation.

Our result also helps to resolve previous contradicting findings in the literature assessing the allocation of capital toward countries with higher productivity (see Lucas (1990) or Caselli and Feyer (2007)). While countries' productivity may be hard to measure and may depend on several factors, our study shifts the perspective toward firms. Capital flows are indeed directed to firms and their MPK can be measured more exactly with accounting data.

Other Wedges. The marginal productivity of capital has several advantages highlighted above, but it may conflate firm productivity and other market wedges. To disentangle the channels we now progressively examine the allocation of capital along the distribution of several wedges. We start with mark-ups, which encompass wedges in market structure or other sectoral nominal rigidities. As explained earlier their calculation requires the estimation of the production function. Since the latter maybe questionable for firms in the financial sector in this case we present results and show their robustness with and without this sector

(Appendix C.5). The correlation, shown in 45, using estimates from both Compustat and Worldscope, is positive and significant again at 95% confidence interval, albeit the coefficient are less precisely estimated compared to the case of MPK.[24] Once again we observe an allocation at the top for both claims and liabilities. The economic magnitude are also meaningful. For instance for liabilities, for which the mean equity share is 0.21, a one standard deviation increase in mark-up implies a 1.7 estimated increase in the portfolio share of the corresponding firm. The estimated increase in the portfolio share is even stronger when we examine the relation with TFP estimated through Olley and Pakes (1996) (a relation that we report in Appendix C): in this case the estimated increase in the portfolio share is 17.11.

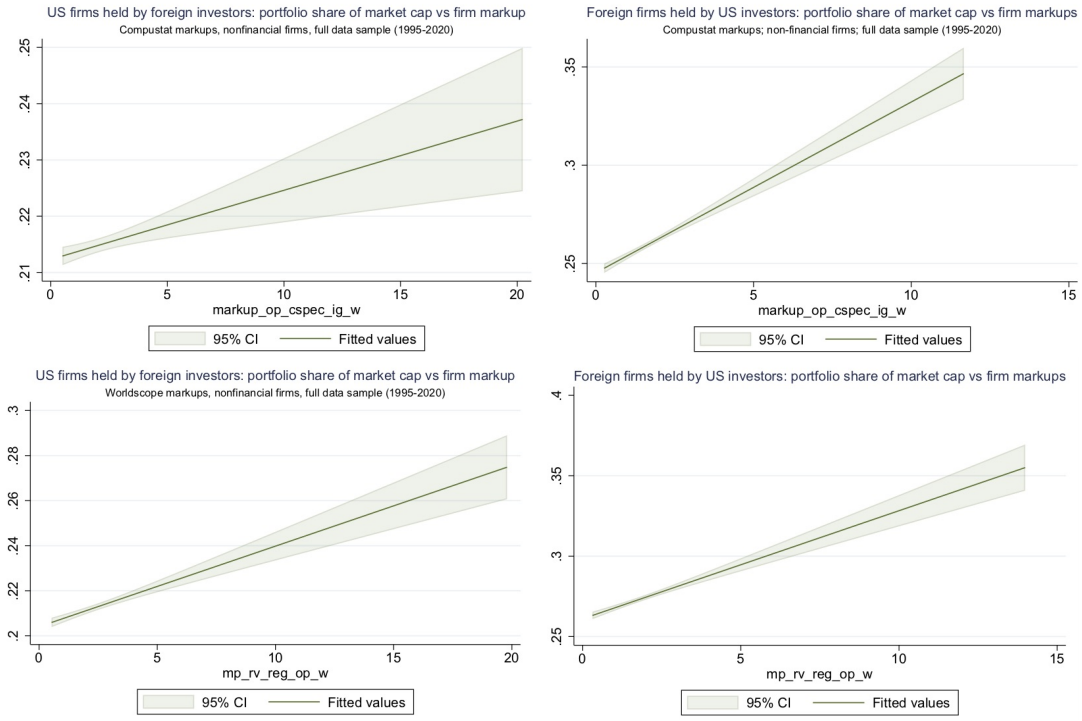
A higher wedge tends to imply a lower size of the firm relatively to the efficient allocation. If so, allocating funds to those firms, and hence rising their growth prospects, brings the allocation closer to the pareto frontier. The underlying force that induce a reallocation to the top are ultimately linked to the "second Marshall law" (see Baqaee and Farhi (2020b)). Demand elasticity tends to be smaller for goods at the top of the distribution. Hence the firms producing them tend to extract large mark-ups. Given their inefficient size those same firms command larger allocation of resources and funds.

Correlation between Excess Returns and Wedges. While the main focus of the firm level analysis lies in the disentangling the allocative role of capital flows, it is of interest to examine also the correlation of excess returns with the firm wedges. This indeed provides two useful pieces of information.

First, it allows us to quantify to which extent wedges affect asset pricing. Frictions induce market incompleteness, which in turn, by preventing arbitrage, leads to a cross section in firm returns. The latter are most likely linked to the wedges that affect firm efficiency. A firm facing larger credit frictions, has to pay larger cost of capital and the latter is reflected in its equity returns by the violation of the Modigliani-Miller. Likewise a firm with large and entrenched monopoly power is more likely to pass the rents onto returns through either dividends or rise in future valuations. Under market incompleteness those differences in equity returns are unlikely to be arbitraged away.

24 Standard deviation of 0,0006748 and 0,0012299 respectively and a t-stat of 12.88 and 3,46 respectively for claims and liabilities.

Figure 15: Figure 45 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities and claims in the TIC dataset with the firm mark-ups estimated through both Compustat and Worldscope data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.



The extent of pass-through of firm rents onto equity returns also provides a firm level foundations of the privilege. We have documented that U.S.investors earn an excess returns on their external position as they invest primarily in equities. We have also seen that their claims are allocated toward firm that earn higher rents. A positive correlation between the excess returns and the firm rents would provide further ground to the origins of the exorbitant privilege, or else the excess returns earned by U.S. investors on foreign positions.

Figure 16 shows the correlations between excess returns, that is the equity return of each security net of the firm market capitalization, and mark-ups in both claims, that is foreign firms, and liabilities, or else is U.S. firms. To provide a comprehensive assessment we also show the correlations across the two accounting datasets that we employ, namely Compustat and Worldscope, and across two different sample periods. As the mark-ups have been rising over time we also expect this correlation to increase over time. For both U.S. and foreign firm the correlation is positive and significant in the later sample. For foreign firms it was so also in the earlier sample, a signal that U.S. investment abroad has usually tended toward firms with both higher mark-ups and higher returns.

Figure 16: **Figure 16 plots the correlation of the equity excess returns (return of each firm equity minus the firm market capitalization), for securities of U.S. liabilities and claims in the TIC dataset with the firm mark-ups estimated through both Compustat and Worldscope data. The cross-sectional regression is estimated using the cross sectional averages on two sample periods 2004-2009 and 2014-2019. Green bands are 95% confidence intervals.**

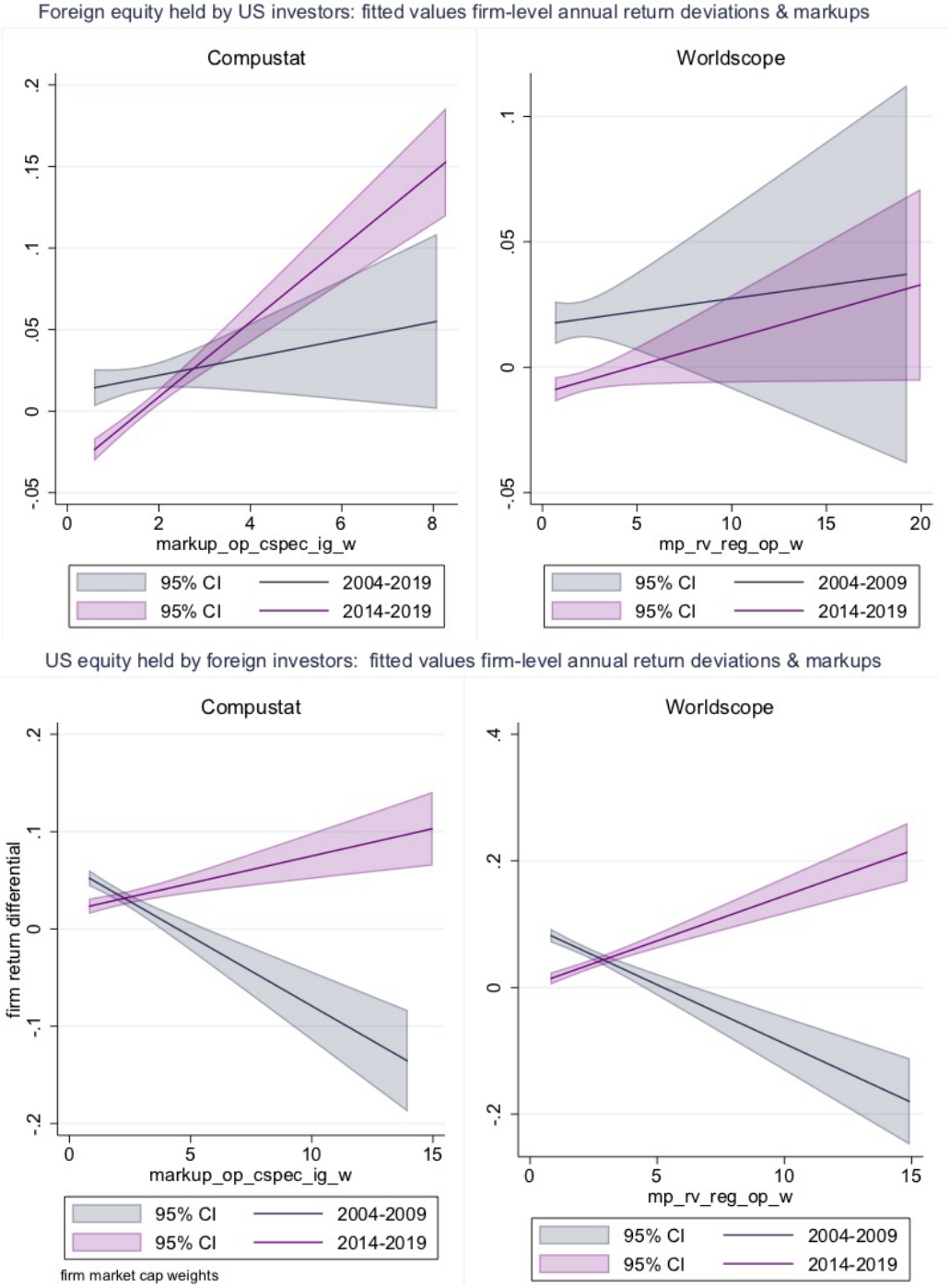
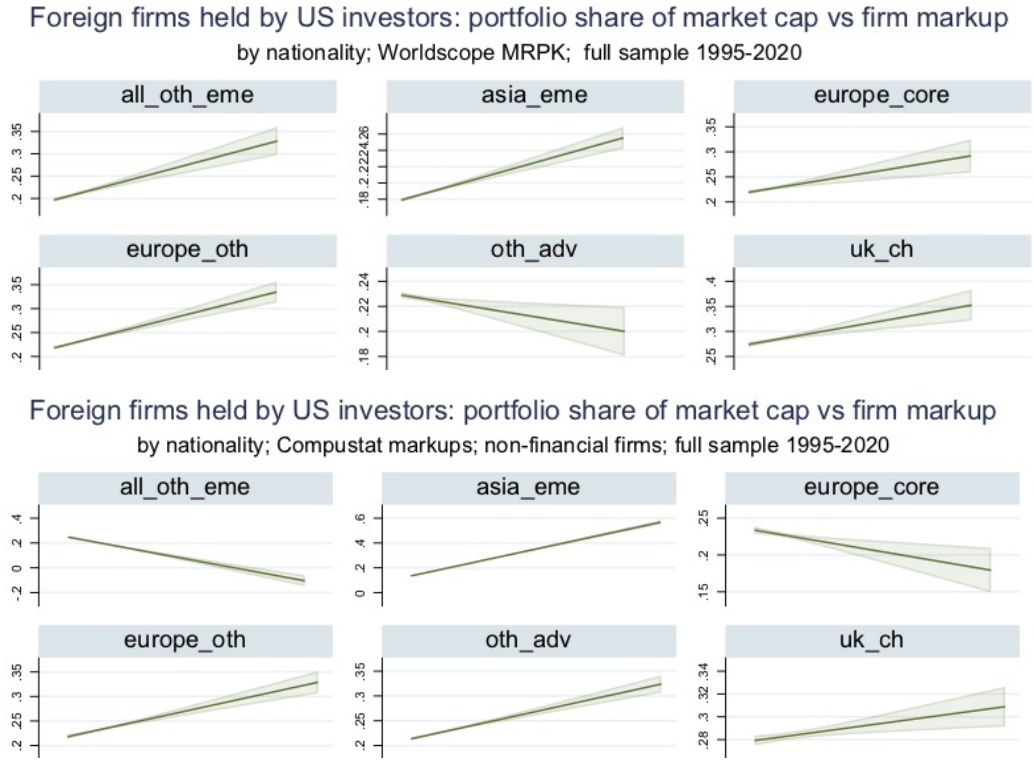


Figure 17: **Figure 17 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities in the TIC dataset with the marginal productivity of capital of the issuing firm estimated through both Compustat and Worldscope data by region. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.**



The Geography of Mis-allocation. Next, for foreign firms held in TIC portfolios we decompose the correlation of portfolio shares onto MPK and mark-ups by region. Results are shown for MPK in figure 17.[25] Figure 45 in Appendix C.5 shows the equivalent but for firm mark-ups. The correlation with MPK is positive and significant for the majority of them and the slope is more pronounced for Asian firms. Before we documented that U.S. investors earn a large part of the returns on claims on Asian firms and that the latter also exhibited large shifts in the productivity and mark-up distribution. This new evidence, coupled with the previous one, shows that the reallocation to the top is actually more pronounced for firms in this region.

Break Down by Sectors. Autor et al. (2020) showed that the reallocation toward firms with higher wedges occurred primarily in growing sectors such as BioTech. In light of this we drill down and reassess our evidence at sectoral level.[26] Results for the correlations with mark-ups are shown in figure 19. The top panels show results for portfolio shares of U.S.

25 We use Worldscope estimates for the first and Compustat for the second with the sole goal of maximizing the data matching.

26 In this case we focus on Compustat data for brevity.

firms and bottom panels for shares of foreign firms. The equivalent correlation with firm productivity, computed through Olley and Pakes (1996) is shown in Appendix C.5.

Foreign investors allocate shares to firms at the top manly in the BioTech and retail industry, while foreign investors do so mainly in the retail sector. Reading the results again through the lens of the mis-allocation literature U.S. investment abroad helps to channel capital toward high mark-up firms in the BioTech sector that would otherwise be too small due to the high mark-ups.

3.3. The Allocative Role of International Flows Relative to Domestic Ones

The allocation to the top that we documented so far prompts the question on the role of international capital flows relative to domestic investment. Traditional motives for external investment include international diversification. Our evidence has uncovered a distinct role in terms of allocative efficiency. We can establish such a role more firmly by comparing the allocation of international flows across the firm distribution to the one of domestic equity holdings. The comparison amounts at a diff and diff design answering the question on the additional allocative role of international securities relatively to domestic portfolio investment.

Figure 20 shows the results of a regression linking domestic equity holdings, computed as market capitalization minus the foreign equity shares for each security, over MPK and mark-ups. The relation is negative and significant at 95%. This is in contrast to international investment which nstead reallocates to the top.

Establishing this role for international capital flows also helps to reconcile previous seemingly puzzling findings on the relation between capital flows and productivity (see Lucas (1990); more recently Caselli and Feyer (2007)). Our study does find a positive correlation between capital flows and MPK by shifting the focus from countries, for which MPK or productivity may be harder to measure, to firms.

Figure 19: **Figure 19 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities and claims in the TIC dataset with the mark-up of the issuing firm estimated through Compustat data. Top six panels show results for shares of U.S. firms and bottom panels show results for shares of foreign firms. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020 for U.S. firms and 2005-2020 for foreign firms. Green bands are 95% confidence intervals.**

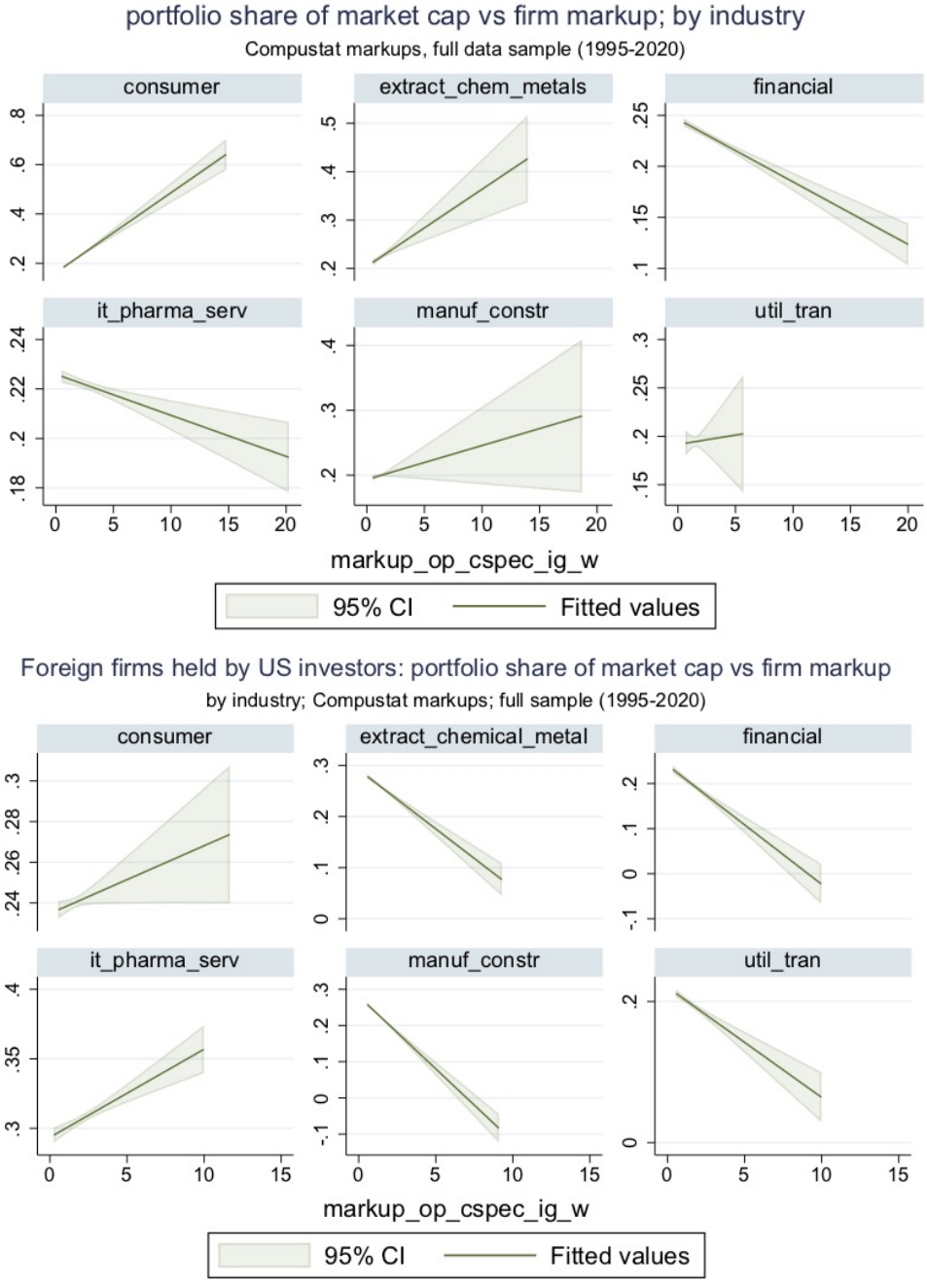
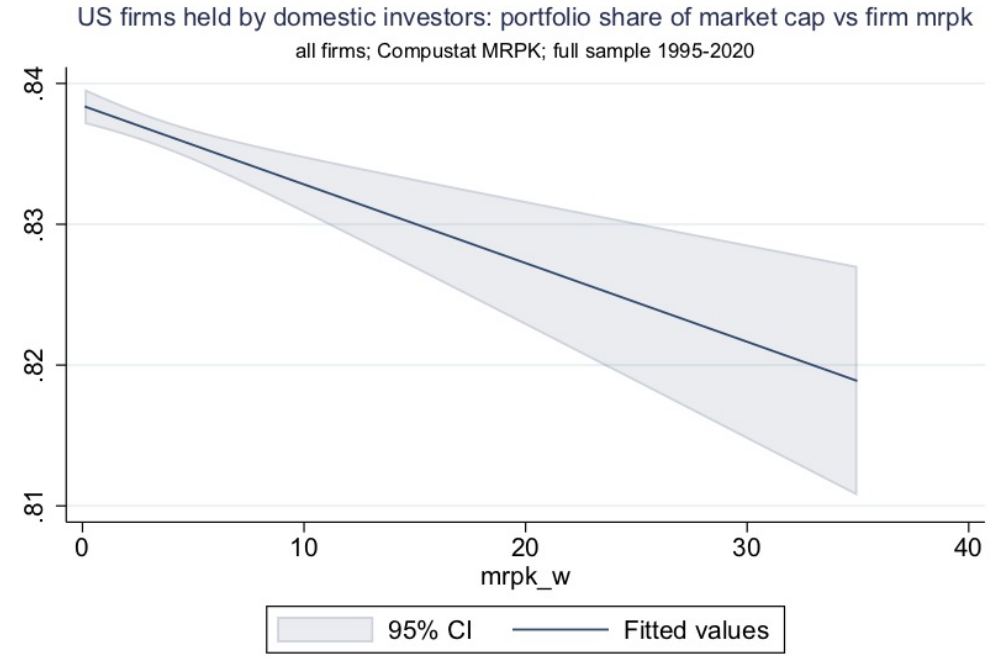
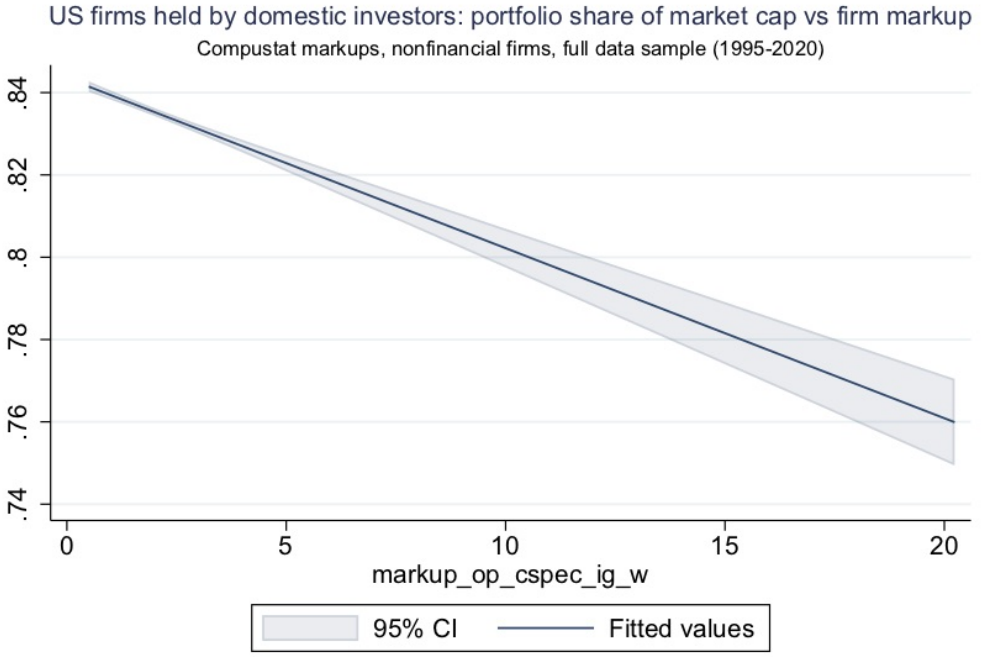


Figure 20: **Figure 20 plots the correlation of the domestic equity share of firm i, for securities of U.S. liabilities and claims in the TIC dataset with the mark-up of the issuing firm estimated through Compustat data. Top six panels show results for shares of U.S. firms and bottom panels show results for shares of foreign firms. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020 for U.S. firms and 2005-2020 for foreign firms. Green bands are 95% confidence intervals.**





3.4. Role of Intangibility

A growing part of the literature attributes the reallocation at the top and the increase in concentration to the growth in intangible capital. First, intangible capital may rise firm MPK, and second returns to intangible capital may appear as pure rents. For instance Autor et al. (2020) or Crouzet and Eberly (2021) document that superstar firms hold both high market wedges as well as high intangible, particularly so in sectors such as BioTech. Crouzet and Eberly (2021) argues that capital returns are shared among workers, capitalists and holders of intangible capital, and the latter may account for the rise in the profit shares that may appear as pure rents.

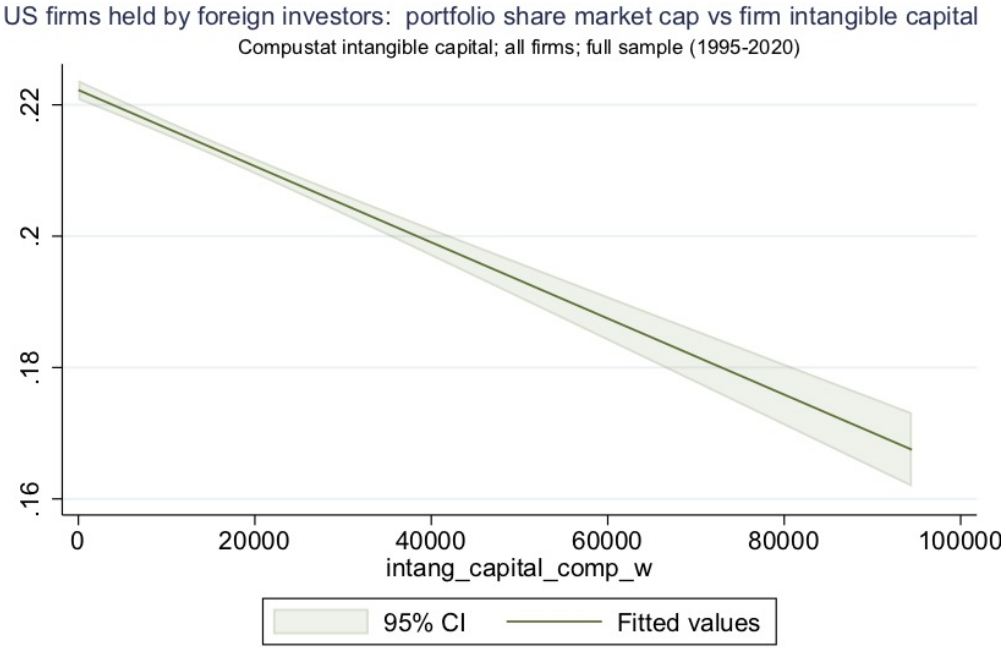
We compute intangible capital following the perpetual method by Peters and Taylor (2017) and apply it to firm accounting data from Compustat for the full time sample 1995-2020.[27]. Results for the usual specification linking individual equity shares, net of market cap, and intangible capital are shown in figure 21. A dichotomy emerges between U.S. and foreign firms of the TIC portfolios. The portfolio shares indeed correlate positively with intangible capital for foreign firms and negatively for U.S. firms. Intangible capital typically signals large growth prospect, hence an allocation of U.S. investment to firms high in intangible improves allocative efficiency. There maybe alternative reasons behind the difference detected on claims and liabilities: U.S. and foreign investors may have different risk-attitudes, something relevant for intangible capital which is often associated with large uncertainty. It may however also signal a difference in the composition of equity portfolios between claims and liabilities. What is relevant for our argument is that, to the extent that intangible capital fosters firm growth, only the U.S. portfolio shares help to improve allocative efficiency.

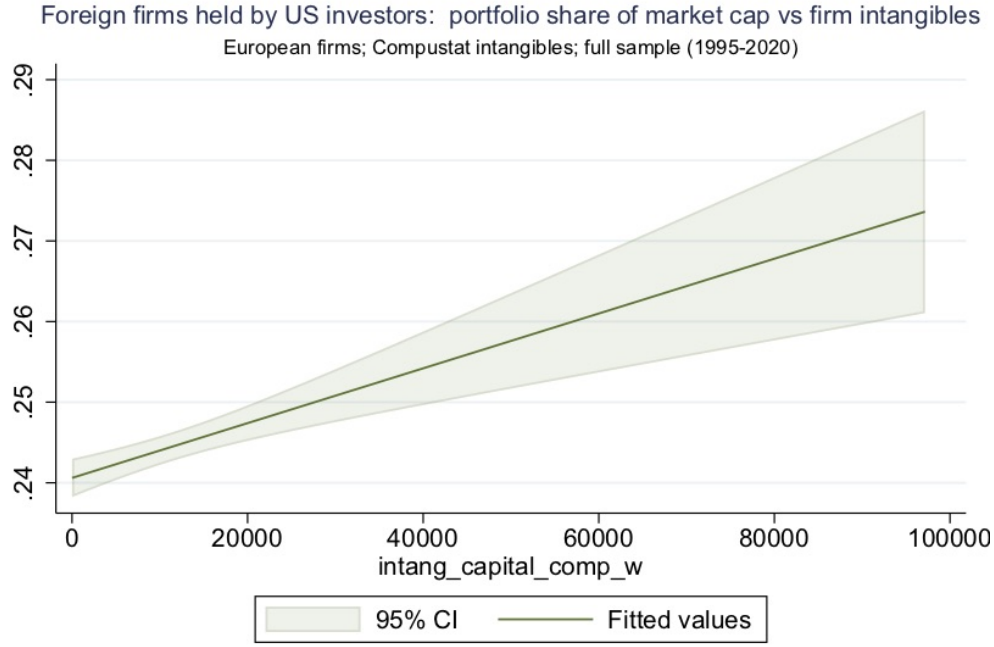
3.5. The Allocative Role of Capital Flows for Credit Frictions

So far we focused on firm productivity and market wedges. However dispersion in financial wedges, or else credit frictions, also induces mis-allocation. We measure financial wedges with distance to default, which signals impaired firm capacity to obtain credit, and examine the

27 The description of how the index is constructed is reported in appendix B. Our measure is very close to the one employed for instance in Crouzet and Eberly (2021).

Figure 21: **Figure 21 plots the correlation of the equity share minus the market capitalization of firm i, for the securities of U.S. claims and liabilities in the TIC dataset with the firm intangibility index using Compustat data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.**





allocation of capital flows along its distribution. Recent literature (Ottonello and Winberry (2020)) has also adopted this measure to quantify the role of credit frictions for firms. In debt contracts with asymmetric information indeed the external finance premium is related to the distance to default. More specifically, the distance to default provides a measure of the distance – in asset value standard deviations – of the current market value of assets in a company from a specified default point. It is derived using information on the market value of assets, a pre-specified default point and the uncertainty of the market value of assets. In the absence of information on the market value of assets, the value of equity and debt in the company are typically used as proxies. We obtain those using Refinitiv data. One of the main assumption when calculating the distance to default is that the company is expected to honour in full its debt obligations to bondholders when the debt matures, otherwise the bondholders take over the company and the shareholders receive nothing. The shareholders of the company choose to refuse to meet the obligations of the company if its assets were to be valued less than its debt and its would honour otherwise. An important aspect to note is that the distance to default may decline when asset values decline relative to debt or when market uncertainty (or volatility) rise. It is important to keep this aspect in mind when examining the results.

Another important aspect to note is that our securities data will be related to distance to default across countries and that the latter may exhibit some composition effects. In countries in which financial institutions or legal systems guarantee better repossession abilities there is higher tolerance to risk and firms will exhibit higher probability of default or fatter right tails in its distribution.[28] To understand the extent of the country composition effects figure 48 in Appendix C.5 plots the distributions of the probability of default for the U.S. and foreign firms whose equities are in the TIC dataset. There is a striking difference in the top tail, which s much larger for U.S. firms, attesting to a much greater tolerance for risk. This may of course be due to preferences, culture or to a higher efficiency of the bankruptcy procedures: as lenders know that they can repossess more they tend to tolerate higher probabilities of default. To purge for those composition effects, in the regressions below we use the distance to default net of the mean or median in each country portfolio.

28 We document this through figures 46 and 47 in Appendix C.5.

Figure 22 shows results for the regression of the equity portfolio shares, in liabilities and claims, on the distance to default, net of the mean per country.[29] In both cases higher shares allocate to firms with distance to default lower than the median, hence with higher probability of default or market uncertainty. Through the lens of the misallocation literature this result shows that international securities allocate toward firms with higher probability of default. Once more this speaks on the allocative role of capital flows, which by easing domestic credit constraints reduces the distance to the pareto frontier. Seen through a lens of a classical portfolio choice optimization however this result may appear puzzling at first as it may imply that investor shares are higher for riskier firms. The optimality of the portfolio shares however is to be judged based on the overall mean-variance optimization. As noted earlier when buying securities abroad investors may likely seek higher returns, and this may come along with higher market risk. The reach for yield may of course also depend on the risk-attitudes of investors in different countries.

To further assess the motives behind the portfolio allocation across countries and its relation to the mean-variance criteria we regress the equity portfolio shares net of market capitalization on the Sharpe ratio, namely the ratio between the mean returns and the variance of the returns.[30] Once again here we net out the Sharpe ratio by its mean per country to purge for composition effects: some countries may indeed have a riskier pool of firms than others. Figure 23 shows results. American investors allocate higher shares to firms that pay higher returns, after compensating for risk. Foreign investors do the opposite. Those results provide further ground to the exorbitant privilege: American investors tend to allocate higher shares to firms that pay higher returns relatively to foreign investors. And it is also more generally in line with the marked allocation to the top that characterizes the portfolio shares of American investors.

29 For this measure our available data sample starts in 2005.
30 To compute Sharpe ratio we use Refinitiv data.

Figure 22: **Figure 22 plots the correlation of the equity share net of market capitalization of firm i for the securities of U.S. claims and liabilities in the TIC dataset with the distance to default, measured from Refinitiv data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 2005-2020. Green bands are 95% confidence intervals.**

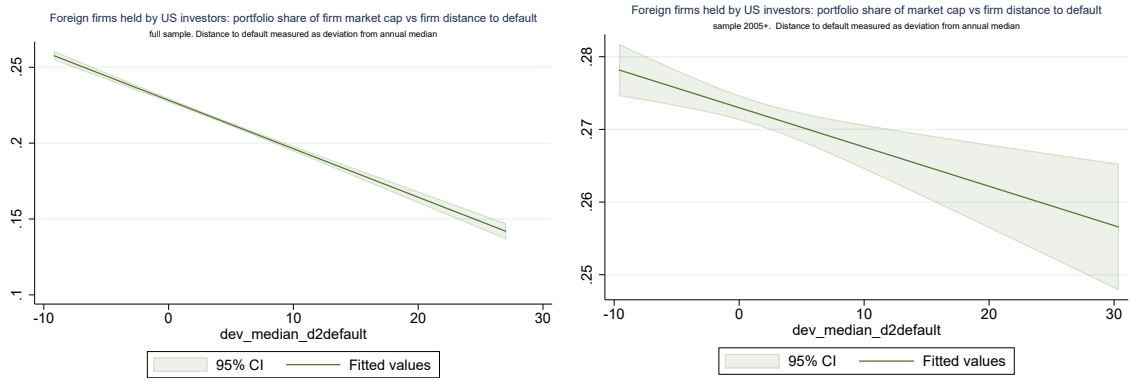


Figure 23: **Figure 23 plots the correlation of the equity excess returns, net of market capitalization, for the securities of U.S. claims and liabilities in the TIC dataset with Sharpe ratios, computed using Refintiv data, over two sample periods, 2004-2009 and 2014-2019. Green bands are 95% confidence intervals.**

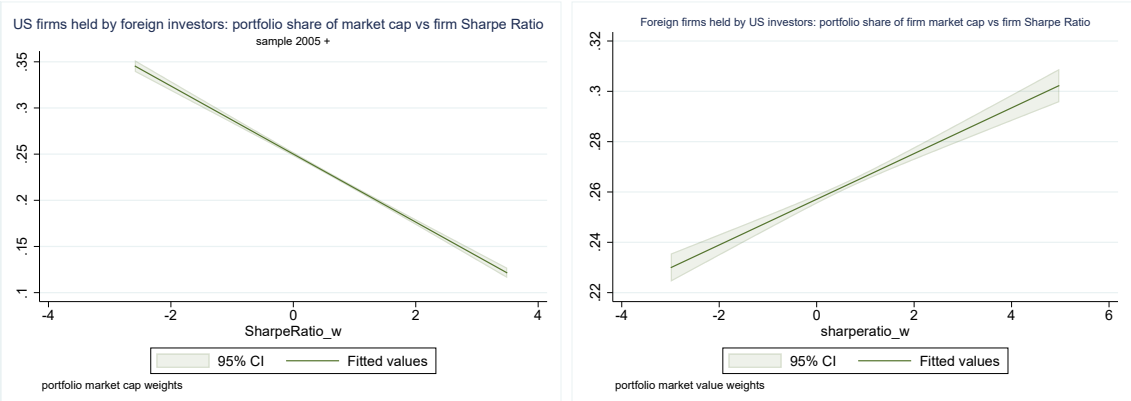


Table 7: **Top table shows growth in market capitalization for U.S. firms (left) and foreign firms (right) across two different time samples, 2004-2009 and 2014-2019, for all sectors of firms in the TIC dataset. Bottom table shows mean and median markups computed with Olley and Pakes (1996) and using Global Compustat data, broken down by industry and weighted by market capitalization across two different time sample, 2004-2009 and 2014-2019.**

	Growth market Capitalization			
	2004-2009	2014-2019	2004-2009	2014-2019
	U.S. Firms		Foreign Firms	
Consumer	15,2%	18,9%	12,5%	17,8%
Oil gas mining metals	12,3%	7,4%.	24,1%	17,2%
Financial	17,5%	14,9%	13,6%	10,0%
It, Electronics, Pharma	35,7%	40,9%	16,5%	24,4%
Manufactur, Construction	9,9%	9,1%	14,9%	17,2%
Utilities, Transportation	9,4%	8,8%	18,4%	13,3%
	Mean and Median Mark-ups			
	2004-2009	2014-2019	2004-2009	2014-2019
	U.S. Firms		Foreign Firms	
Consumer, Mean	1,37	1,40	1,52	1,89
Consumer, Median	1,27	1,30	1,42	1,39
Oil, gas, mining, Mean	1,15	1,11	1,43	1,40
Oil, gas, mining, Median	0,87	0,88	1,29	1,18
Financial, Mean	2,16	3,60	1,35	1,99
Financial, Median	1,67	2,44	1,30	1,89
It, electronics, pharma, Mean	2,67	2,83	2,30	2,27
It, electronics, pharma, Median	2,05	2,03	1,77	1,81
Manufactur, construction, Mean	1,09	1,12	1,28	1,33
Manufactur, construction, Median	1,01	1,04	1,12	1,12
Utilities, transportation, Mean	1,54	1,46	1,78	1,51
Utilities, transportation, Median	1,63	1,52	1,49	1,36
Total, Mean	1,95	2,30	1,62	1,76
Total, Mean	1,41	1,47	1,34	1,34

4. The Dynamic Reallocation to the Top

Some past papers have examined and documented an increasing trend in market concentration in the form of reallocation to the top: Melitz and Ottaviano (2008), Autor et al. (2020), De Loecker and Warzynski (2012), Baqaee and Farhi (2020b) are just some examples. So far we have found that equity shares are allocated to the top. We are now interested in assessing the time changes of this reallocation. We do so by computing rolling windows of a within and between firm decomposition of the wedges weighted by individual equity shares. Specifically for two firm measures, namely MPK and mark-ups, we compute the following weighted aggregate:

$$FM_t = \sum_i s_{i,t}^{net} \omega_{i,t} \tag{16}$$

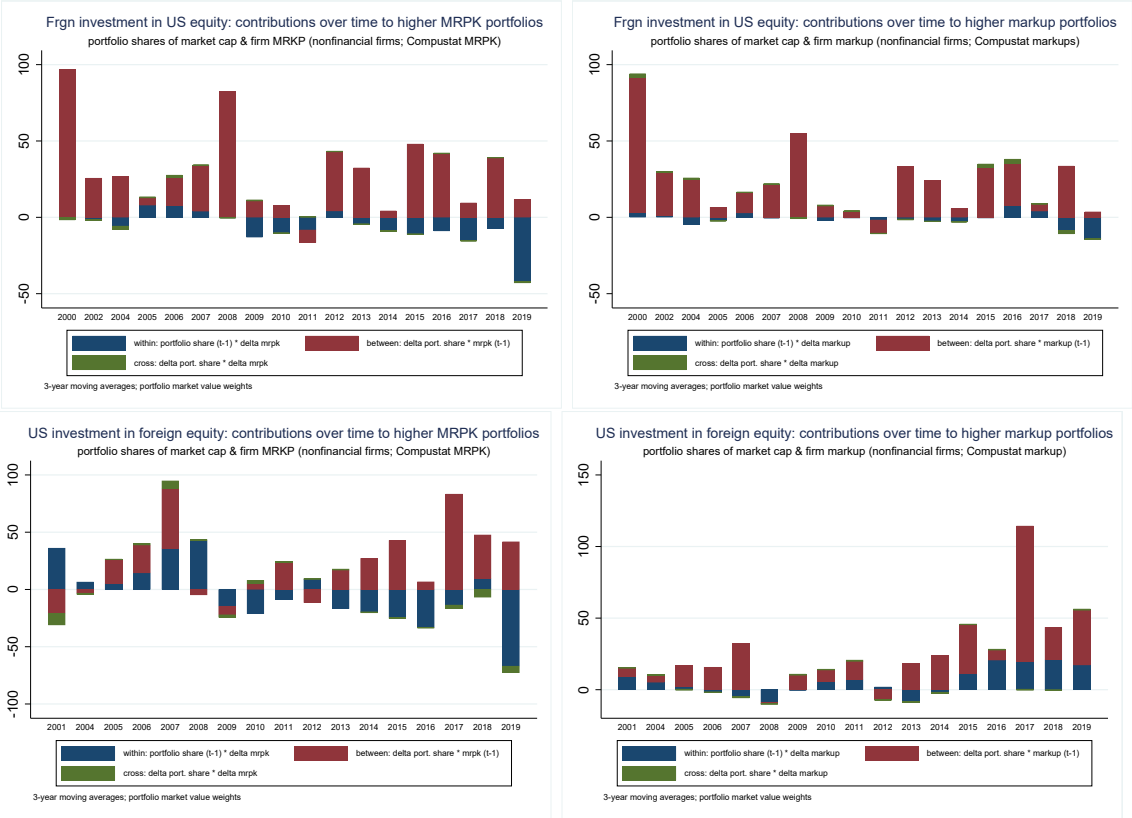
where $s_{i,t}^{net} = s_{i,t} - \overline{s}_{i,t}$ is the portfolio share of individual equity shares for each firm net of market cap and $\omega_{i,t}$ is the corresponding firm measure. The weighted changes in the measure FM_t is then decomposed as follows:

$$\begin{aligned} FM_t - FM_{t-1} &= \sum_i s_{i,t}^{net} \omega_{i,t} - \sum_i s_{i,t}^{net} \omega_{i,t} = \\ &= \underbrace{\sum_i s_{i,t-1}^{net} (\omega_{i,t} - \omega_{i,t-1})}_{\text{within term}} + \underbrace{\sum_i (s_{i,t}^{net} - s_{i,t-1}^{net}) \omega_{i,t-1}}_{\text{between term}} + \\ &+ \underbrace{\sum_i (s_{i,t}^{net} - s_{i,t-1}^{net})(\omega_{i,t} - \omega_{i,t-1})}_{\text{cross-term}} \end{aligned} \tag{17}$$

The within term of the decomposition indicates changes over time of the individual firm measure. The between term indicates a reallocation toward firms that are higher in the distribution of the corresponding firm measure, hence it captures the notion of reallocation to the top. The cross term captures the loop between the two: firms with higher MPK tend to grow faster, place themselves at the top of the distribution and may command larger shares. For the reasons mentioned above we focus on firms in Compustat and we exclude financial firms.

Figure 24 plots the decomposition over time for both U.S. firms, hence firms in liabilities,

Figure 24: **Figure 24 plots the changes in the within, between and cross terms of the within-between decomposition in for both MPK and mark-ups. over the sample period 1995-2020 for both U.S. firms, hence for firms in liabilities, and foreign firms, hence for firms in claims.**



and foreign firms, hence firms in claims, and for both MPK and mark-ups. First the between firm component is prevalent. Second, the same between term changes over time. It declines for U.S. firms and it rises for foreign firms, highlighting the more pervasive role of reallocation to the top for U.S. firms investment abroad.

5. A Horse Race to Assess Predictive Power of Firm Characteristics for Capital Flows

So far our research interested lied in assessing whether a reallocation to the top and for each of the firm measures separately. Econometrically this also guarantees that the information provided by each of the firm measures does not overlap with others. The firm level regression for each firm measures alongside the dynamic decomposition are well suited in our view to address whether a reallocation along the firm distributions has taken place. Our results however also calls into question which of the firm variable are more likely to predict future

trends in capital flows. We address this next through a methodology that combines a panel regression and a "horse race" with an in-sample forecast. Broadly speaking the panel specification regresses the portfolio shares (net of market cap) onto some firm measures over part of the sample, that is up to 2015; the horse race is then obtained by regressing the actual portfolio shares in 2020 over the predicted variables for each of the firm variable as estimated up to 2015.

Specifically, we first estimate a set of panel regressions which portfolio shares (net of market cap) are regressed on several firm measures as well as firm and time fixed effects for U.S. firms in the liabilities and then for foreign firms in claims. For the second, as firms may differ significantly across geographic regions we run our regressions separately for Emerging Market Economies (including Asia) and for Europe and other advanced economies.[31] Formally the econometric specification reads as follows:

$$s_{i,t} - \overline{s}_{i,t} = \gamma + \sum_i \alpha_i x_{i,t} + f_i + f_t + \epsilon_{i,t} \tag{18}$$

where f_i and f_t are firm and time fixed effects (when we break down the foreign firm by region we also include a region fixed effects) and where the regressors $x_{i,t}$ include a set of firm measures, which are MPK, mark-up, intangible capital, TFP, and distance to default, all estimated in Compustat data and by excluding financial firms. These measures are only imperfectly correlated, hence it is perfectly legitimate to include them jointly in a multi-variate panel regressions. Additionally the estimates of all five measures are significant at 95% confidence interval.

Figure 25 plots the single-variable relationship of a panel regression of the portfolio shares (net of market cap) over time and firm fixed effects and over the following firm measures: MPK, mark-ups, TFP, intangible capital and distance to default for each of 3 regions (US, emerging markets, and Europe other advanced). These are all done on consistent samples (relationships for firms where all 5 variables are available in any given year). The results

31 We exclude UK firms as they appear to have significant noise and the estimates are hard to generalize. It is also the case that U.K. has very different regulation than the rest of the European block. For the firm in Europe and other advanced economies, we also include a dummy since the mean portfolio share is higher for to this group.

of the panel regression largely confirm the results we observed so far with the individual regression. There is reallocation to the top of the MPK, TFP and mark-up distribution for both U.S. and foreign firms, while for intangible capital this is true only for foreign firms held by U.S. investors in advanced economies. Beyond confirming our previous findings, the new results are useful to produce in-sample forecast for the allocation of capital flows. We do so with the second stage which consists of an horse race along the line of Fair and Shiller (1990).

Specifically our horse race is implemented as follows. We estimate through 2015 the fixed effect econometric models, each relating the portfolio shares to each of the firm variables. We then forecast the firm-specific portfolio share in 2020 and calculate estimated change in portfolio share between 2015 and 2020. Finally, we regress the actual change in the firm level portfolio share on various pairs of estimated changes (markup vs MPK, markup vs intangible capital, markup vs TFP, etc).[32] Formally the regression reads as follows:

$$\tilde{s}_{i,t} - \tilde{s}_{i,t-1} = \alpha + \beta_1(\hat{s}^1_{i,t} - \hat{s}^1_{i,t}) + \beta_2(\hat{s}^2_{i,t} - \hat{s}^2_{i,t}) + \epsilon_t \tag{19}$$

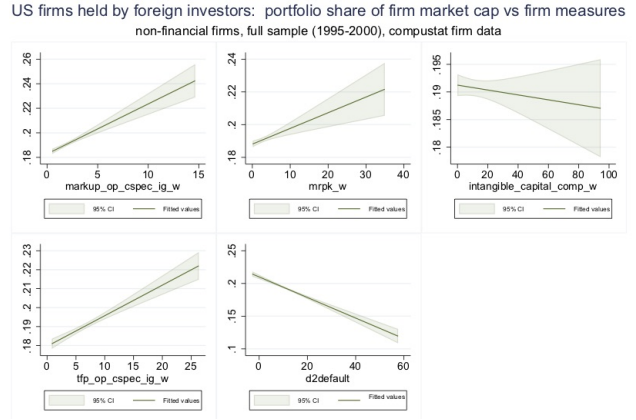
where $\tilde{s}_{i,t} - \tilde{s}_{i,t-1}$ is actual change in portfolio share from 2015 to 2020 and where $\tilde{s}_{i,t}$ is the portfolio share of firm i net of its market cap, and where $\beta_j(\hat{s}^1_{i,t} - \hat{s}^j_{i,t})$ are estimated changes in portfolio share, where the 2020 value is estimated from a panel regression using only one firm measure at a time, and only up to year 2015.

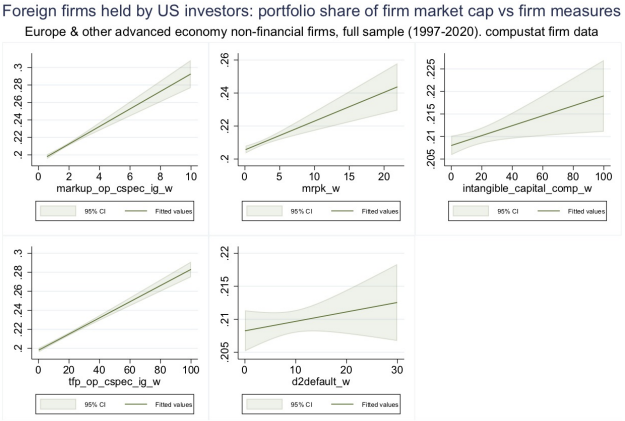
Results are reported in Table 8. The table shows our five measures aligned in pairs and reports which coefficient (if any) is significantly different from zero for each regression pair, and at what confidence interval. As an example if the actual change of portfolio share is regressed on MPK and TFP we report which of the two coefficients is significant and their significance level. This indeed tells us which firm measure in the pair has more information for the (future) change in portfolio share.[33] If neither have predictive power, then we report this event with "—" sign.

32 Since the firm-level error terms are generally non-zero mean, we assumed that these were equal to the firm-level mean error term over the sample through 2015.

33 Note that while both measures in the pairs may have significant coefficients as reported in the full sample panel regression, it may be the case that only one of the two provides somewhat more information for the forecasts.

Figure 25: **Figure 25 plots the single-variable relationship of a panel regression of the portfolio shares (net of market cap) over time and firm fixed effects and over the following firm measures: MPK, mark-ups, TFP, intangible capital and distance to default for each of 3 regions (US, emerging markets, and Europe other advanced). These are all done on consistent samples, that is samples for which all 5 variables are available in any given year.**





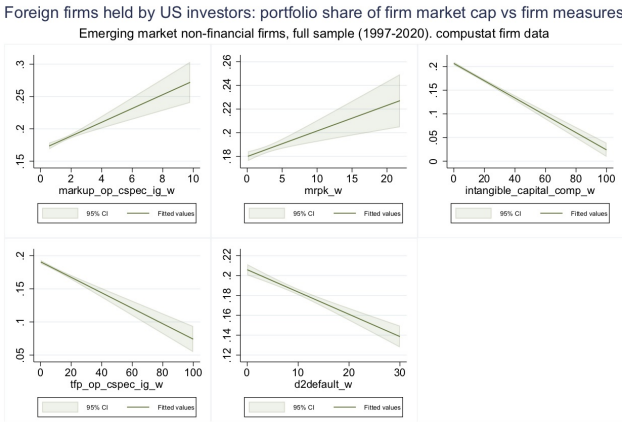


Table 8: Horse race for contributions of different components. Change in portfolio share from 2015 to 2020. Estimates from a regression of actual change in portfolio share (at firm level) over estimated portfolio share in 2020 - actual in 2015; estimates for 2020 are based on estimation through 2015. Top panel is for U.S. firms, hence liabilities, and bottom panel is for foreign firms, hence claims. The latter are divided in two regions: Europe and Advanced Economies and Emerging Market Economies plus Asia. * significance 10%, ** significance at 5%, * significance at 1%. Ae stands for Advanced Economies and it includes Europe, EME stands for Emerging Market Economies and it includes Asia.**

Models; U.S. Firms	MPK	Intangible Capital	TFP	Distance to Default
markup	mpk*	markup***	tfp***	–
mpk		mpk***	tfp**	mpk*
intang capital			tfp***	d2d***
tfp				tfp***
Models; AE Firms	**MPK**	**Intangible Capital**	**TFP**	**Distance to Default**
markup	–	markup***; int**	markup***	markup*** ; d2d***
mpk		mpk*** ; int**	mpk**	mpk*** ; d2d***
intang capital			int*** ; tfp*	int*** ; d2d***
tfp				d2d**
Models; EME Firms	**MPK**	**Intangible Capital**	**TFP**	**Distance to Default**
markup	–	int*	tfp**	markup* d2d***
mpk		–	–	mpk** ; d2d***
intang capital			–	int** ; d2d***
tfp				tfp** ; d2d***

For US firms held by foreign investors, results suggest added information comes mostly from TFP, and in some cases from MPK. For firms in Emerging Market Economies (EME), distance to default matters, but also the other variables especially intangible capital and TFP. For firms in Europe and other advance economies, pretty much all seem to matter.

6. Conclusions

Using a confidential dataset of the universe of all U.S. security claims and liabilities, we re-examine the portfolio return differential over time, across regions and sectors. Given the highly dis-aggregated nature of our data we can go beyond the average portfolio returns and uncover the variations underlying them.

At the level of portfolio returns we find that the excess return between U.S. claims and liabilities is positive and stable on average and is due the composition of claims which are tilted toward equities. The average portfolio equity returns are very similar across countries,

while the bond returns are still lower for U.S. liabilities, albeit mostly vis-a-vis countries with high sovereign default risk. Exploiting the geographical dimension of our data we find that equity portfolio shares have increasingly shifted toward Asian firms, particularly so for those channelled through Caribbean centers.

Next we examine the allocative role of capital flows by exploiting the disaggregated nature of our data and by matching the portfolio shares to firms' MPK and other wedges. Overall through both the correlations and a panel regressions of the equity shares with the wedges, as well as the time-varying decomposition in their within-between components, we find that equity shares aim to the top, uncovering a new role for capital flows in terms of allocative efficiency. The results also reconcile previous puzzling findings on the link between capital flows and productivity by shifting the focus from countries to firms.

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

Aggregate Statistics. The TIC (Treasury International Capital) system collects data on cross-border banking and securities positions and transactions. These data form the basis for official U.S. 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). Reporting is legally mandated.

Responsibility for the TIC system is shared by the U.S. 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 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 U.S. residents' debt and equity claims against foreign residents (that is, foreign securities held by U.S. residents) and on U.S. debt and equity liabilities to foreign residents (that is, U.S. 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 U.S.-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 https://home.treasury.gov/data/treasury-

international-capital-tic-system-home-page/tic-forms-instructionsbenchmark. Specifically the dataset reports the break down of the claims and liabilities per equity, debt, Treasuries and officials covering all countries in the U.S. 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.

Confidential Securities Level Data. The confidential portion of the data has so far never been used. Computing returns at security level required to match each security with the corresponding price. For equity the price and the dividend are reported in the SHL survey. For bonds the price has been retrieved by matching the corresponding security CUSIP or ISIN from Bloomberg. Note that the data reports not only whether the asset is debt or equity, but also the type of debt (its duration, maturity). It is indeed the case that each firm issue one equity, but it can issue several type of bonds. This data covers the period 2005-2020.

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

The foreign securities holdings of U.S. residents (claims) and the U.S. securities holdings of foreign residents (liabilities) are collected by the U.S. 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 U.S. 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 U.S. 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 U.S. claims include U.S.-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 U.S. -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 U.S. 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 U.S. 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 U.S. liabilities include U.S.-resident custodians, including brokers and dealers and U.S. central securities depositories, and U.S.-resident issuers. Institutions must report all U.S. 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 U.S.-resident custodian even if the securities are in turn held at DTC, Euroclear, or another central securities depository. U.S.-resident issuers must report all securities issued by U.S.-residents which are not held at a U.S.-resident custodian or central securities depository. Firms must report a

security ID (CUSIP), description, issuer name, security type, currency, type of U.S. 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.

A.2. Computation of Portfolio Returns Across Methods

We compute portfolio returns in four ways, namely by by security, using external indexes, and from the BEA published reports in two ways.

Security-Level. The annual return on each security is calculated using a standard calculation and the prices obtained from the annual surveys and the interest and dividend payments obtained from outside sources: Return (security-level) = (price end – price start + interest or dividend payments)/price start. The returns are aggregated by asset type using weights calculated from holdings at the start of each survey year. The liabilities returns are as of June 30 of each year to match the liabilities surveys, claims returns are as of December 31 of each year to match the claims surveys.

Index. The index-based return uses country-level MSCI equity and similar bond total return indexes to estimate the annual returns. Aggregates are constructed by weighting the index returns by the share invested in each asset in each country. The liabilities returns are as of June 30 of each year to match the liabilities surveys, claims returns are as of December 31 of each year to match the claims surveys.

BEA. The method is based on inferring the returns from tan approximation of the net foreign asset positions at time t, NFA_t, or else the difference between foreign assets and liabilities. The latter can be written as:

$$NFA_{t+1}R_{t+1}NFA_t + NX_{t+1} \tag{20}$$

where the first term on the right side is the return on foreign investment and the second term is the trade balance. Equation 20 states that the net foreign position increases with net exports and with the total return on the net foreign asset portfolio Rt+1. Dividing through by GDP at time t, and using lower case letters to denote normalized variables one obtains:

$$nfa_{t+1} = \frac{R_{t+1}}{g_{t+1}} nfa_t + nx_{t+1} \tag{21}$$

where g_{t+1} represents the growth rate of output between t and $t+1$. Gourinchas and Jeanne (2006) employ the above relation both in the steady state and in forward iterations to examine the long run returns and also how the adjustment follows a shock to exchange rates. Data from BEA NFA as asll as financial market indeces are used to compute some of the relations. We replicate their method.

Specifically, we use published BEA data to compute returns by asset class in two ways. The first is more precise because it uses BEA's valuation adjustment calculations to compute capital gains: Return (BEA ret) = (valuation adjustment + income) / holdings (start). The valuation adjustments are from BEA IIP table 1.3, income from BEA transactions table 4.1. The second method can be constructed for a longer time period but uses a less precise inference of capital gains based on the difference in start- and end-year positions: Return (BEA raw) = (holdings end – holdings start – flows + interest or dividend payments)/holdings start. Holdings are from BEA IIP table 1.2, flows from BEA Transactions table 1.2, income from table 4.1. Both the liabilities and claims returns are as of December 31 of each year because BEA data are reported annually at year end.

A.3. Remapping residence-based holdings to firm nationality

We use the method of Bertaut et al. (2019) to remap the securities from their country of residence to the country of nationality. We use security-level identifiers and text-matching techniques to map each security to the country of exposure for each firm as assigned by commercial products designed for international investors, thus converting these holdings to a "nationality" basis. Because information on security identifiers is inconsistent in our data,

especially in earlier years, we use text matching to assign nationality to securities for which we cannot match by security identifiers. We extensively clean security names and then use exact and fuzzy matching techniques.

For common stock equity holdings, we rely primarily on the constituent information for Morgan Stanley Capital International (MSCI) country-focused equity indexes, supplemented with information on the primary location of operations for firms that are not included in the MSCI indexes. For common stock, we manually assign the ultimate MSCI country designation for securities of companies that have not yet been included in an MSCI index. For example, we assign any U.S. holdings of Chinese firms such as Alibaba, Tencent, and Baidu (incorporated in the Cayman Islands) to China for years prior to 2015, although these firms were not included in the MSCI China/Emerging Markets indexes until 2015.

For bonds, we also rely on information about the ultimate parent company obtained from Moody's Investors Service, and, for asset-backed securities, about the underlying assets to map holdings of corporate bonds to a nationality basis. Our reassignment primarily affects corporate debt. Although sovereign bonds of many countries are issued as international debt securities, their country assignment typically will not be distorted in residence-based statistics in the same manner as corporate bonds, because they are not issued via subsidiaries that are legally incorporated in offshore financial centers. Our reassignment to "ultimate parent" nonetheless results in a few differences in country for government debt securities. Some of these differences arise from debt securities that are primarily repackaged sovereign debt exposures. Additionally, some bonds were misclassified by country in the underlying data. Because our underlying data are from the surveys of U.S. portfolio holdings of foreign securities collected on a residence basis, we are not able to include U.S. investor holdings of bonds issued by U.S. financing arms of foreign firms.

We remap U.S. cross-border fund shares and other equity holdings using "mirror data" on the portfolio assets of countries that account for the majority of such U.S. cross-border holdings, most notably the Cayman Islands, Ireland, and Luxembourg. For fund share and other equity allocations, we rely primarily on country allocations of financial center reporting

to the CPIS, as their outward CPIS statistics will largely reflect the underlying securities of investment funds incorporated in those locations.

A.4. Computing Returns from the indexes

The procedure used to compute the portfolio weights follows Curcuru et al. (2008). Specifically, indices were chosen by comparing security-level holdings with publicly available returns indices. The returns on a country's U.S. bond portfolio using a weighted average of Lehman Brothers U.S. Treasury, corporate, and agency bond indices, with the weights being that country's portfolio weights in each respective bond type. It is important to use the actual weights of foreign investors in the four types of bonds to produce an accurate measure of their returns on U.S. bonds, as those weights may actually vary substantially from weights in a market-capitalization benchmark. For returns on U.S. equities we use the return on the gross MSCI U.S. index, a market-capitalization-weighted index composed of roughly 300 large and liquid U.S. equities, as typically held by international investors. Returns on foreign equities are proxied using dollar returns on the gross MSCI equity index for each country. As already argued in Ammer et al. (2004) MSCI firms represent almost 80% of U.S. investors' foreign equity investment. As for returns on foreign bonds, a currency bias has already been noted in the past (see Burger and Warnock (2007)). For this reason we choose returns of local bonds in dollars. For developing countries this means the JPMorgan's EMBI+ indices (which are composed of dollar-denominated bonds). For developed countries we distinguish those in which U.S. investors do not hold significant amounts of bonds. For those we choose the MSCI bond index (which is an index of local-currency- denominated bonds). In developed countries where U.S. holdings of dollar-denominated bonds are significant, we calculate returns as the weighted average of the MSCI bond index and MSCI Eurodollar Credit index (which is an index of dollar- denominated bonds), with the weight on the Eurodollar index being the share of dollar-denominated bonds in U.S. holdings of each country's bonds.

B. Data Used for Estimation of MPK, Productivity and Market Wedges

From both Global Compustat and Worldscope we obtain balance sheet measures from 1990 to 2020 for net sales, wage cost in Compustat and cost of good sold in Worldscope, 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 WorldBank, 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. Four different specifications are employed to estimate the production functions and, consequently, TFP and price markups: Cobb-Douglas as in Olley and Pakes (1996), Cobb-Douglas as in Levinsohn and Petrin (2003), Translog as in Olley and Pakes (1996), with the Ackerberg et al. (2015) correction, Translog as in Levinsohn and Petrin (2003), with the Ackerberg et al. (2015) correction.

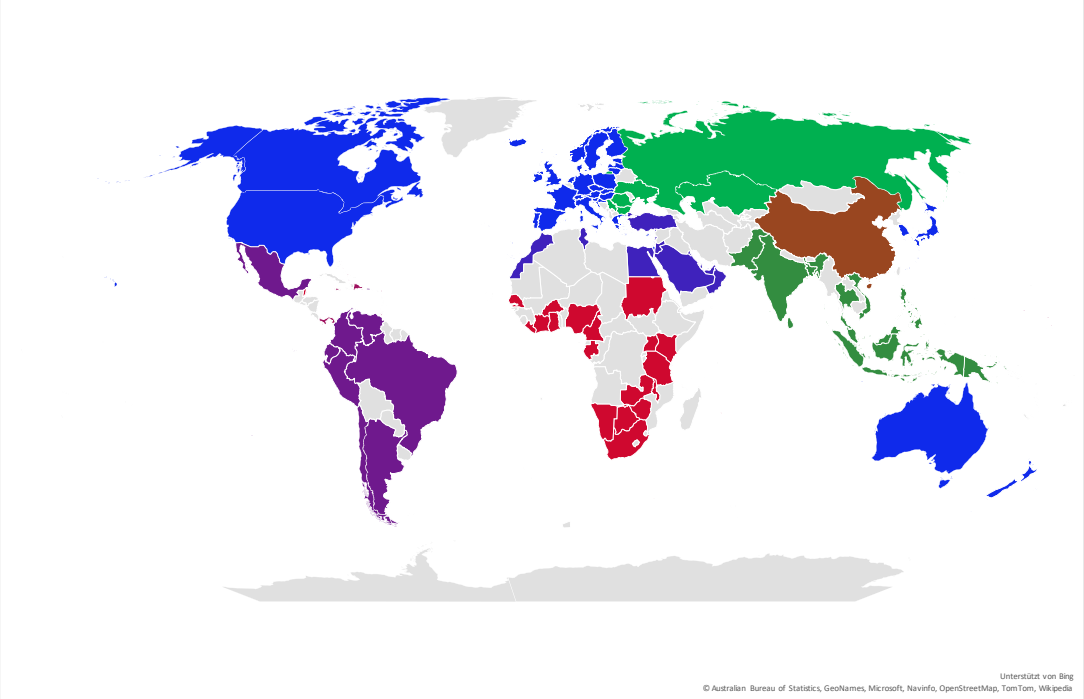
For each specification, estimates are provided for both the case of using revenues as dependent variable and value added (the difference between revenues and cost of goods sold. The free input variable is always labour[34] (WC01084), while the state input variable is capital[35]. The proxy variable is investment for Olley and Pakes (1996)s specifications, and intermediate goods for Levinsohn and Petrin (2003). A notable exception is the case of the Revenue-based, Olley and Pakes (1996) Translog specification, that delivers exclusively negative price mark-ups and for which the *prodest* command fails to deliver TFP estimates. For these reasons, such specification is not included.

We drop firm-quarter observations if sales, costs of goods sold, or fixed assets are only

34 For the sake of consistency: given the balance sheet information available, labour is the only suitable candidate for the Levinsohn and Petrin (2003) specifications. This is why it is employed as well for the Olley and Pakes (1996) ones, even if intermediate goods would be a feasible alternative.

35 And to be precise gross capital, for it has significantly less missing values than its net counterparts and estimates are not significantly different upon making the opposite choice.

Figure 26: **Country grouping for estimation of regional elasticities.**



reported once in the associated year. We further drop observations if quarterly sales growth is above 100% or below -67% or if real sales are below 1 million USD. We finally drop the bottom and top 5% of the estimated markups. We construct a measure of the capital stock of firms using the perpetual inventory method. We initialize $K_{i,0} = ppegtqi_0$ and recursively compute $K_{i,t} = K_{i,t1} + (ppentqi_t - ppentqi_{t1})$.

Finally, intangible capital is computed starting from Selling, General and Administrative Expenses.

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 U.S. 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 U.S. sectors to assess the plausibility of the magnitudes.

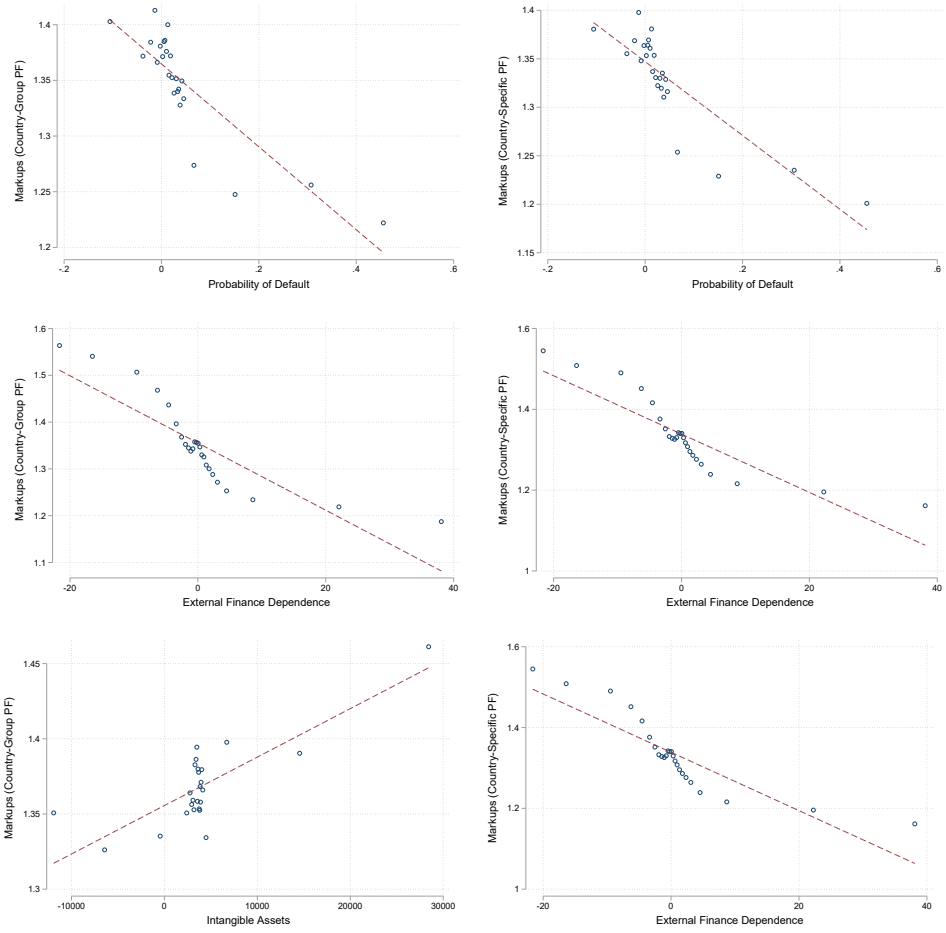
Matching Between TIC and Firm Identifiers. The matching between TIC securities and firm identifiers passes through the Worldscope identifier as in Bertaut et al. (2021). Specifically we first apply a cross-walk from gvkey in Compustat and Worldscope identifiers. We then match the latter with the ISINs 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.

Relation between Mark-ups and Other Firm Measures. In this section we compute correlation among the firm measures and plot the related scatter plots. The correlations are also informative on the patterns that characterize firms worldwide. The correlation are computed by regressing one mark-ups onto other measures and by including country fixed effects.

Figure 27 shows the estimated relations also considering different methods to compute elasticities. More specifically, elasticities are computed either at country level or per group of similar countries. This allows to alleviate the problem of low number of observations. Reassuringly results are robust between the two methods. For this exercise we are using the firm measures estimated using Global Compustat data. Similar results emerge when the measures are computed using Worldscope data.

Mark-up correlates positively with intangibility and negatively with probability of default and external finance dependence. The relations are reasonable. We would expect firms with large share of intangible, such as BioTech, also being the ones extracting larger rents. Those firms are also the ones that default less and that depend less on external finance, as they can reinvest much of their dividends.

Figure 27: **Relation between mark-ups and other firm measures, namely probability of default, external finance dependence and intangibility. The production function is estimated either across group of countries (left panels) or per each country (right panels). The regression includes country fixed effects. The plots are binned scatter plots showing the corresponding mean of each bin. The sample consists of all firms in all countries across all years (1987-2020) and variables are winsorized at 5% before binning. All plots control for country and year fixed-effects (hence some values can be negative, i.e. intangibles for example). The time-series plots show medians across the corresponding sample of countries and each year.**



B.1. Average Mark-ups over Time Across Firms: Compustat and Worldscope.

Figure 28 compares average mark-ups, aggregated by market shares, for all firms included in Compustat and Worldscope aggregating them across world regions. For robustness we also provide this ranking comparing different methods, namely Olley and Pakes (1996) and Levinsohn and Petrin (2003).

We choose two different grouping for the regions. The first is in line with the same groups examined in our regional returns. The second includes a selection of the largest economies in Europe, Asia and other Emerging Markets.[36] Mark-ups for firms in every region is then compared to mark-ups of U.S. firms. First, mark-ups across different regions are in similar ball parks. Contrary to conventional wisdom it does not appear that the U.S. has extremely larger average mark-ups than others. All have increased over time and increase in concentration seems to be a global trend.

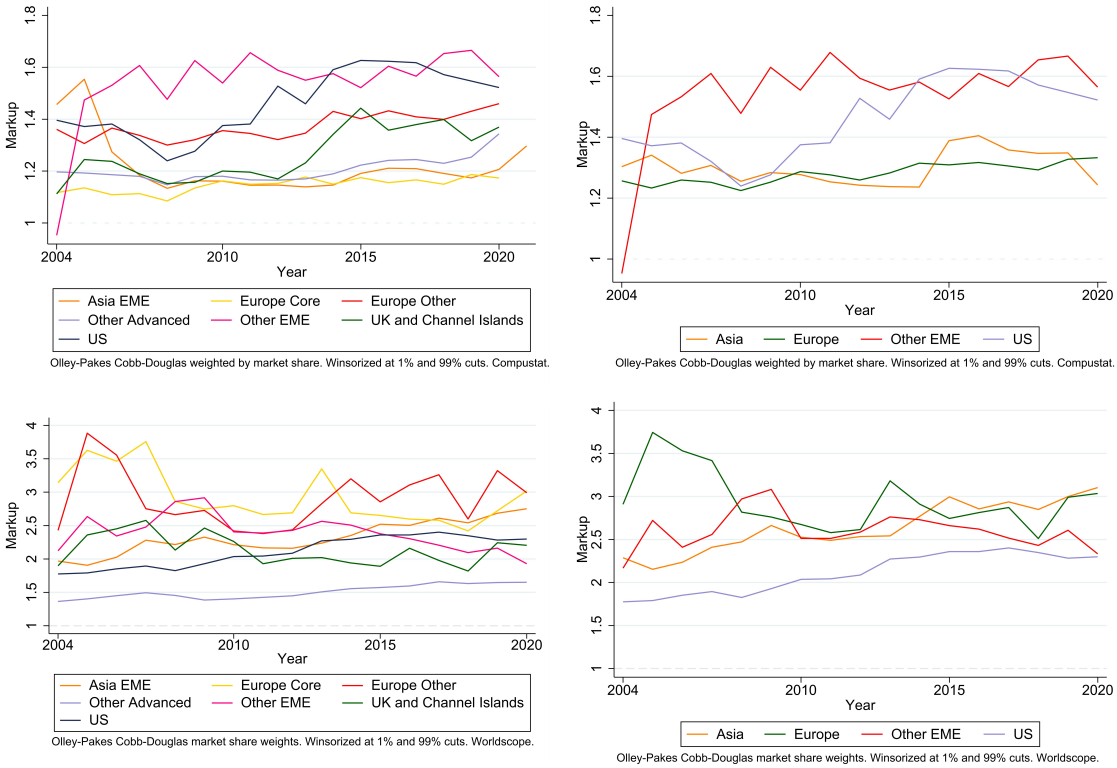
B.2. Firm Distributions in Compustat and Worldscope

In this section we presents some statistics for firm measures across different datasets and estimation methods. This exercise serves two purposes. First, we are interested in uncovering the trends in firm dynamic across regions and over time even beyond the ones observed in the TIC matched dataset. Second, comparing the distributions across different datasets and methods allows us to establish the trends that are common to the two and hence robust. We focus in particular on examining the average mark-ups, weighted by market shares, across regions and the kernel distributions, also across regions. While we estimate all firm measures across both datasests here we present a selection of results which are representative across the two.

Production function estimation is done using both Olley and Pakes (1996) and Levinsohn and Petrin (2003). The average appears to be trending up significantly for the U.S. as

36 The groups of countries are as follows. Europe includes Austria, Belgium, Denmark, Germany, France, Ireland, Italy, Portugal, Norway and Spain. Asia includes: China, Hong Kong, India, Philippines. Other Emerging Market includes: Argentina, Brazil, Chile, Colombia, Mexico and Peru and European Eastern block, namely Check Republic, Hungary, Poland, Romania, Turkey, Slovak, Slovenia, Russia and Kazakistan.

Figure 28: **The figure plots average mark-ups, weighted by market shares, for all firms in Global Compustat (left panels) and Worldscope (right panels). Mark-ups in Compustat are estimated based on Olley and Pakes (1996) and assuming a Cobb-Douglas production function. Mark-ups in Worldscope are estimated in two fashions, with Olley and Pakes (1996) and Cobb-Douglas production function and with Levinsohn and Petrin (2003) and Cobb-Douglas production function. The figures refers to two grouping of countries. The top is the same group of countries shown in the regional returns. The second is an alternative group of countries**



documented by De Loecker and Warzynski (2012), but so did for other world regions. This too confirms previous evidence by De Loecker and Eeckhout (2018). The rise of mark-up in Asia is remarkable and in part larger than in U.S.

Figures 30 and 32 plot kernel densities of firm productivity and mark-ups, for all firms in Worldscope across different regions.[37] In both cases production function elasticities are computed using value added and by employing either the Olley and Pakes (1996) or the Levinsohn and Petrin (2003). To appreciate the changes in the trends of the distribution the latter is plot for two different years, 2000 and 2019. The world regions considered are U.S., China, Northern Europe, Southern Europe, Western Europe, Southern East Asia. First, the distribution of mark-ups and productivity has shifted forward everywhere and in most cases the shifts are significant based on Kolmogorov-Smirnov tests. The most remarkable shifts are observable for the for mark-ups in China.

37 for this exercise we have chosen Worldscope given its larger coverage worldwide.

Figure 30: **The figure plots kernel densities of firm productivity, for all firms in Worldscope across different regions. Productivity is computed using value added and by employing ether the Olley and Pakes (1996) or the Levinsohn and Petrin (2003). The density is computed for two different years, 2000 and 2019. When not available 2000 is replaced by 2005. Regions are: U.S., China, Northern Europe, Southern Europe, Southern East Asia.**

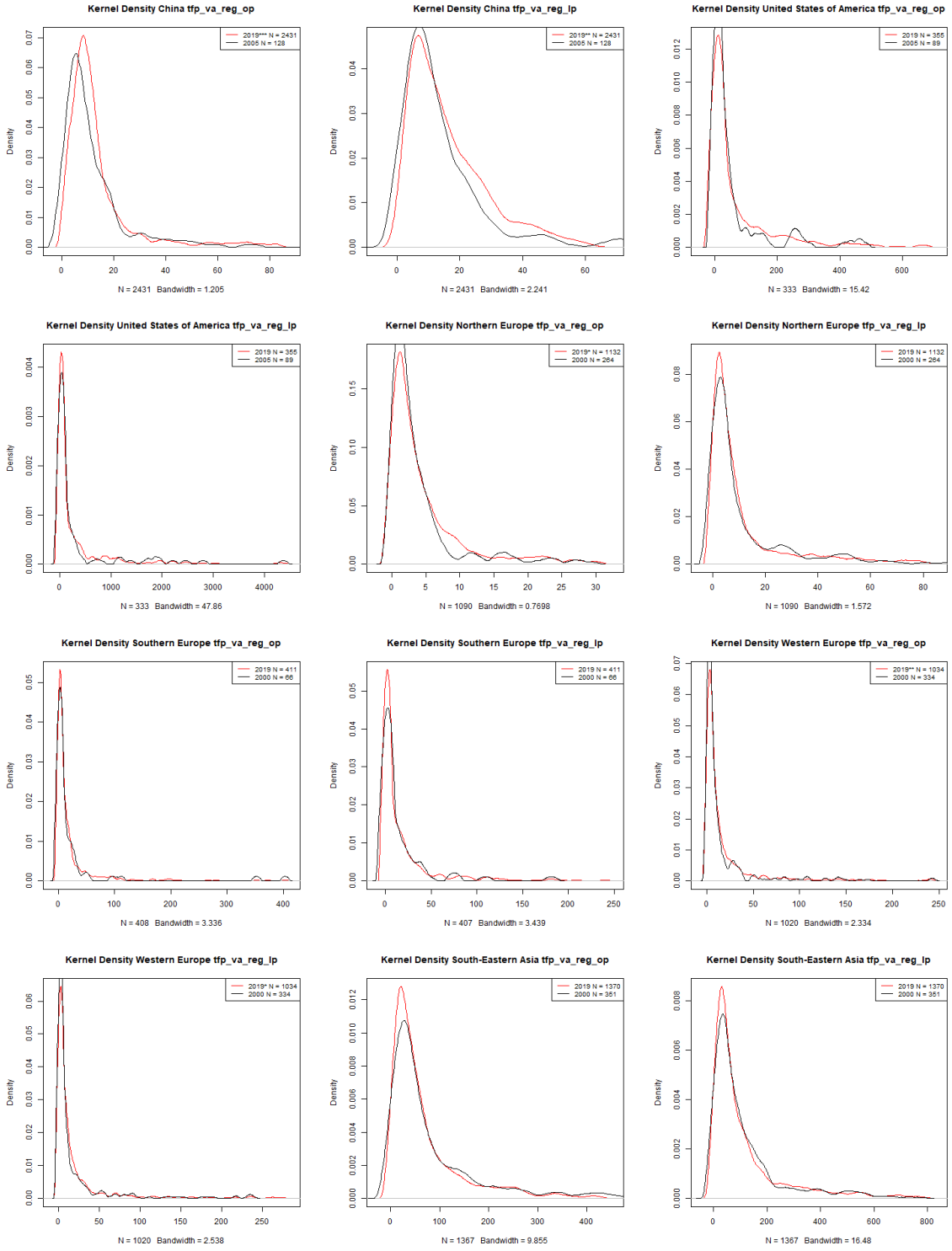
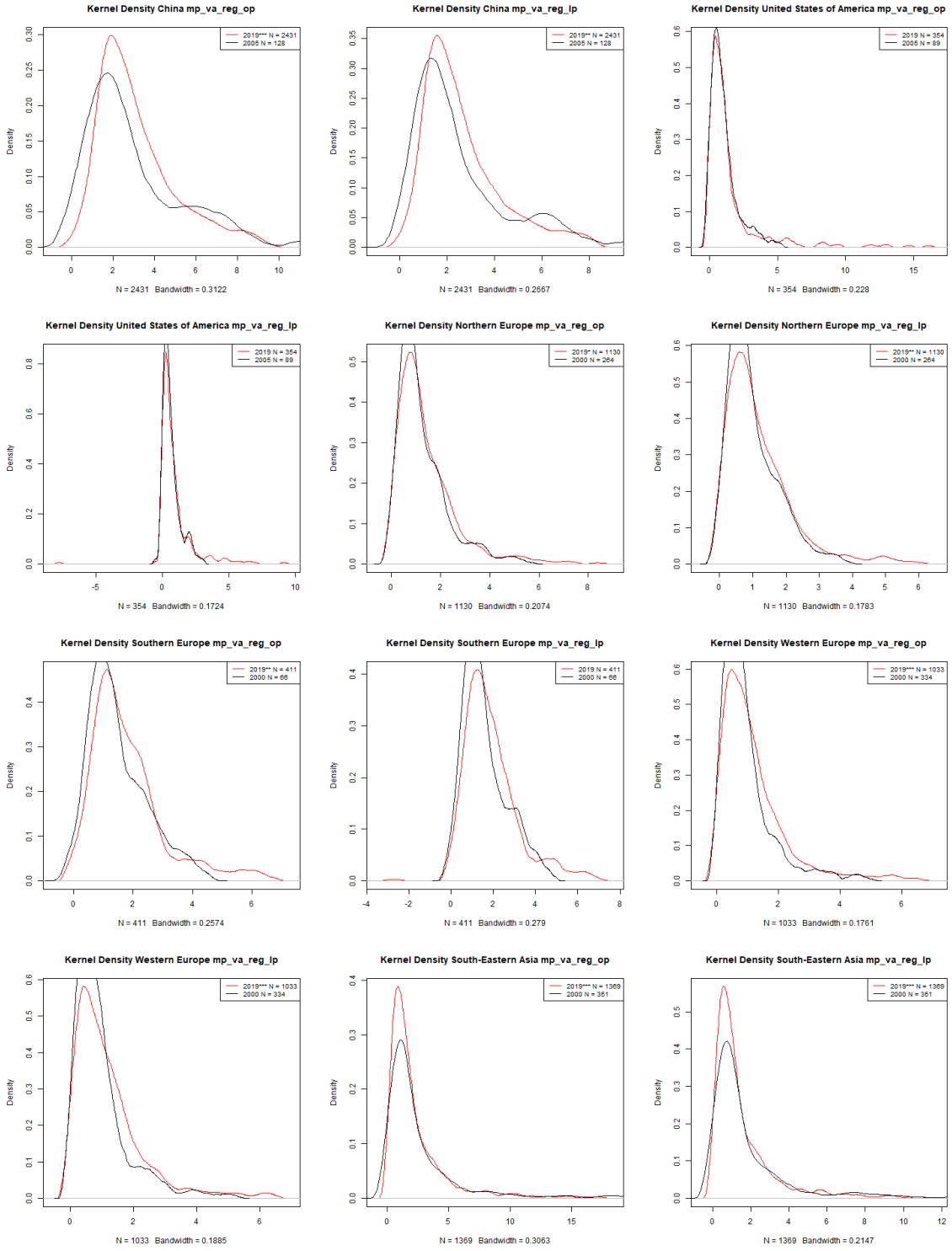


Figure 32: **The figure plots kernel densities of firm mark-ups, for all firms in Worldscope across different regions. Productivity is computed using value added and by employing ether the Olley and Pakes (1996) or the Levinsohn and Petrin (2003). The density is computed for two different years, 2000 and 2019. When not available 2000 is replaced by 2005. Regions are: U.S., China, Northern Europe, Southern Europe, Southern East Asia.**



C. Other Results from TIC Data

The Tables below shows further calculations on the average returns per asset class, across methods and across time samples.

C.1. Comparison Portfolio Returns Across Trend Methods: Hamilton, Hodrick Prescott and Moving Average.

As mentioned earlier the three methods for computing differentials are bound to start at different dates, due to data availability. For robustness reasons we now recompute the trends using Hamilton (2018) methods, which among other things, alleviates concerns related to starting date.

Figure 34 shows a systematic comparison for claims and liabilities of the two trending methods, namely the Hodrick-Prescott filter, for which we choose a smoothing parameter of 6.25 based on Ravn and Uhlig (2002), and the Hamilton (2018) one. The latter is obtained by regressing the variable at date $t + h$ on the four most recent values as of date t, and has several advantages, but most important for us is that it is less sensitive to the starting point. The Hamilton (2018) exhibits by construction more variation, however, once again the trends are broadly aligned across trending methods.

The same similarity applies to the trend returns across methods when we drill down across asset classes. Figure 35 plots the trends, computed using the two filters and all three return measures, for equity claims and liabilities and for bonds claims and liabilities. Further information is provided in Table 12 through the sample averages across trending methods. Once again all returns are trending up in the later sample. For equities this maybe due to a rise in capital gains and for Treasuries this is due to the recent rise in the yields. The rise in the cost of Treasuries is visible also in figure 36 that plots the trend, with both methods, for

Table 9: **Comparison of average portfolio returns over the full sample computed across three methods, that is using the BEA method, the MSCI index (left panel) and one computed using security level data (right panel). Unbalanced panel 1995-2020. Security-level and index liabilities returns are July-June to match liabilities survey. Differential calculation, which are returns on claims minus returns on liabilities, are based on average of current and following year.**

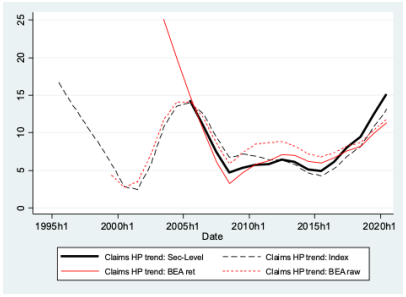
	Index	Security-Level	BEA ret	BEA raw
Claims return	8.48	7.99	9.26	8.48
Liabilities return	7.15	6.12	6.28	5.53
Differential	1.52	1.52	2.98	2.95

Table 10: **Comparison of average portfolio returns over the full sample computed across three methods, that is using the BEA method, the MSCI index (left panel) and one computed using security level data (right panel). Unbalanced panel 1995-2020. Security-level and index liabilities returns are July-June to match liabilities survey. Differential calculation, which are returns on claims minus returns on liabilities, are based on average of current and following year.**

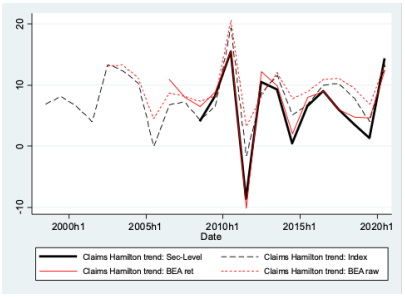
	Index	Security-Level	BEA ret	BEA raw
Equity claims return	9.56	9.32	10.46	8.61
Equity liabilities return	11.22	9.71	9.80	8.04
Bond claims return	6.52	4.73	6.20	8.14
Bond liabilities return	5.11	4.05	3.92	3.90

all bond liabilities broken down by corporate, Treasuries and agencies. At large however the various methods do not deliver economically significant differences.

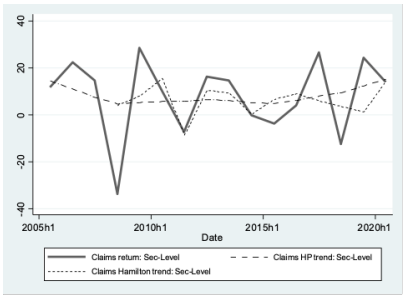
Figure 34: **Trend returns for claims (left panel) and liabilities (right panel) using security level data de-trended with Hodrick-Prescott filter with a smoothing parameter of 6.25 and with Hamilton (2018). See Table 1 for definitions.**



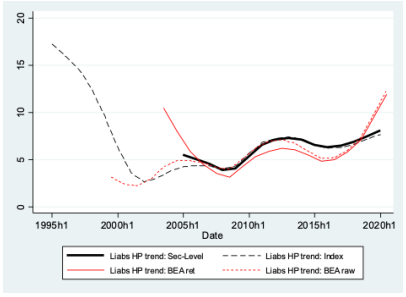
Claim Returns, HP



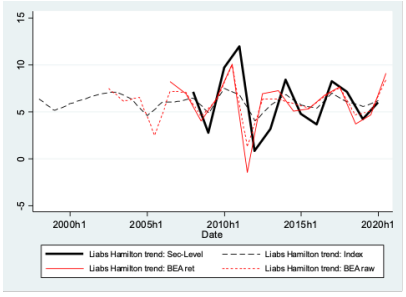
Claim Returns, Hamilton



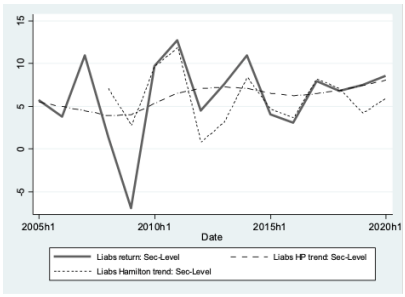
Claims HP vs Hamilton



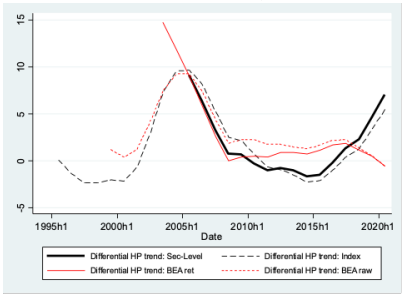
Liabs Returns, HP



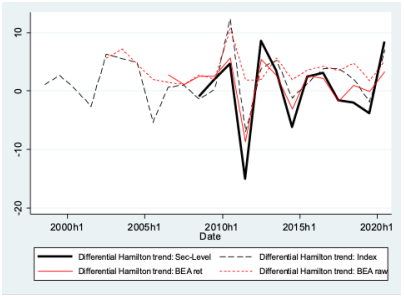
Liabs Returns, Hamilton



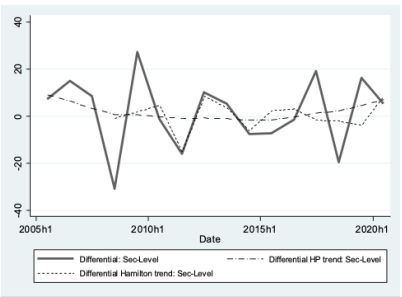
Liabs HP vs Hamilton



Differential, HP

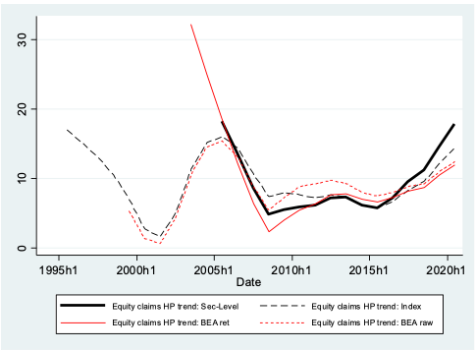


Differential, Hamilton

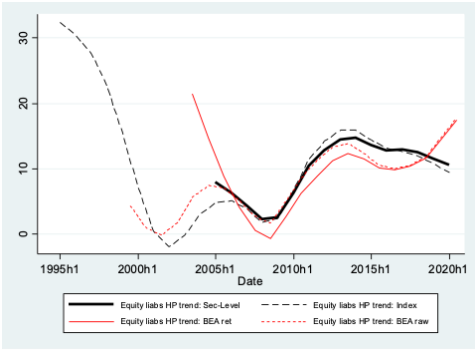


Differentials HP vs Hamilton

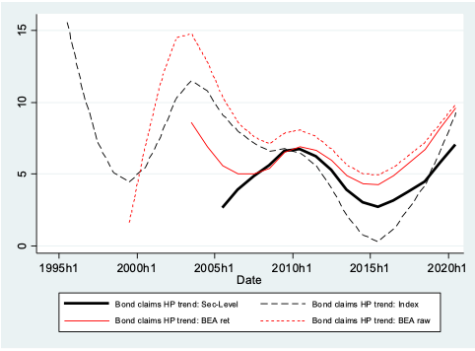
Figure 35: **Trend returns for claims (left panel), liabilities (right panel) and their differential (bottom panel) using the security-level data. See figure 1 for definitions. Hodrick-Prescott filter smoothing parameter is 6.25 based on Ravn and Uhlig (2002). Alternative filter is based on Hamilton (2018).**



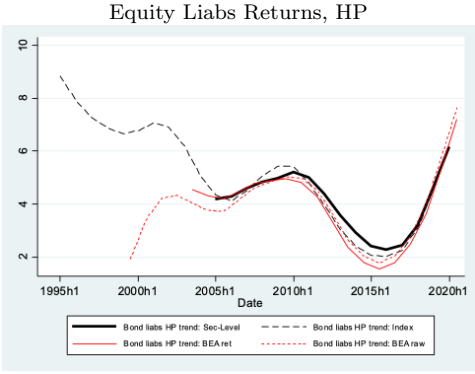
Equity Claims Returns, HP



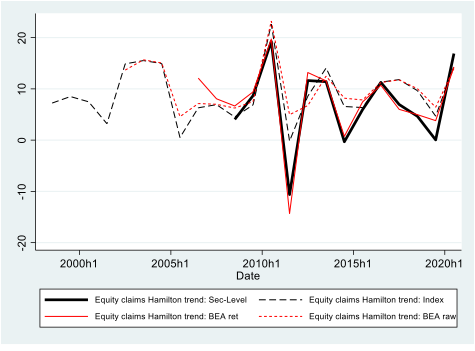
Equity Liabs Returns, HP



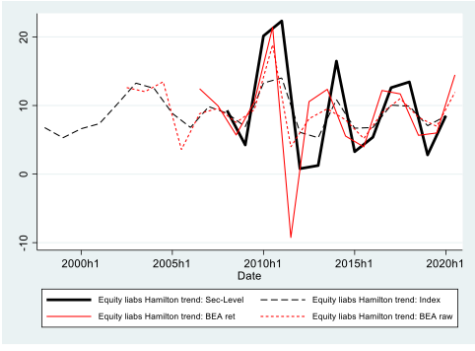
Bond Claims Returns, HP



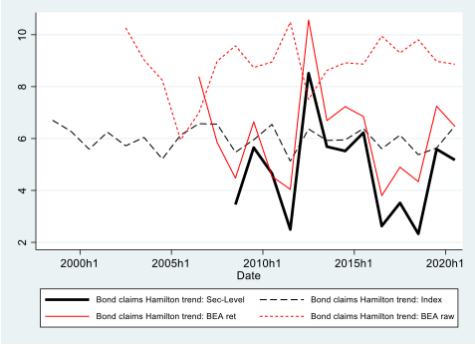
Bond Liabs Returns, HP



Equity Claims Returns, Hamilton



Equity Liabs Returns, Hamilton

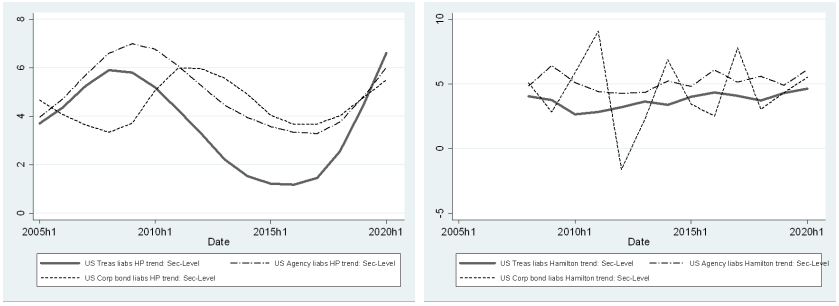


Bond Claims Returns, Hamilton



Bond Liabs Returns, Hamilton

Figure 36: **Trend returns for bond liabilities broken down in corporate bonds, Treasuries and agencies. Left panel shows Hodrick-Prescott filter, while right panel shows Hamilton (2018) trend.**



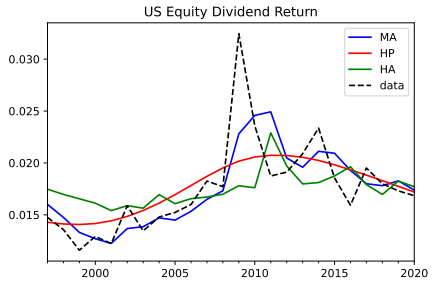
Bond Claim Returns, HP

Bond Liability Returns, Hamilton

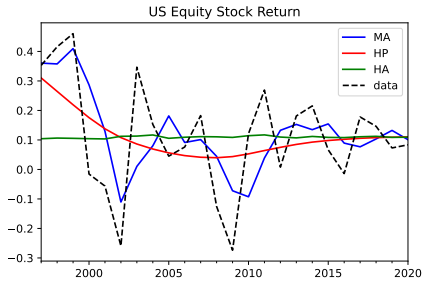
C.2. Extended Time Trends.

While the time series for the modern TIC surveys date back to 2003, less frequent surveys were also taking place in earlier years. Specifically surveys took place in 1997 and 2001 on foreign firms and in 1994, 2000 and 2002 for U.S. firms. An extended time series provides additional information on the long run dynamic. Hence employing data from available surveys we extend portfolio returns backward to 1995. For the missing years we adopt the following imputation procedure. If a firm is active throughout the sample we keep it in the portfolio returns. Operationally if a firm is in both the 1997 and the 2000 survey and it appears as an active firm in other datasets, such as Compustat, we keep it in the computation of the returns. Note also that earlier surveys do not provide the returns themselves, but only the firm identifier. Hence for those we match equity returns, computed as dividends and capital gains, using Refinitiv data.

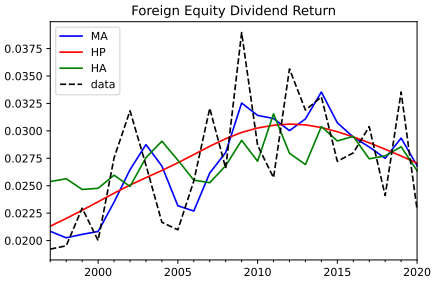
Figure 38: Moving Average of Equity portfolio dividends and returns (computed as dividends and capital gains) in claims, hence foreign firms, and liabilities, hence U.S. firms, for the period 1995-2019. Data on returns for returns are from Refinitiv database and are matched with TIC firm identifier.



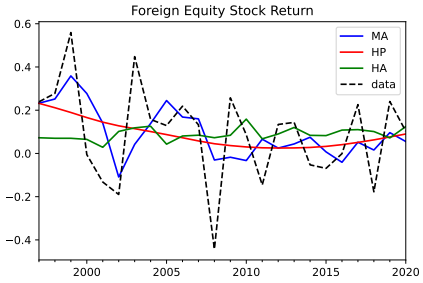
Moving Average U.S. Equity Dividends



Moving Average, U.S. Equity Returns



Moving Average U.S. Equity Dividends



Moving Average U.S. Equity Returns

First, given our interest in eventually linking the equity returns to firm measures we on the equity portfolios, both in claims and liabilities. Second, to avoid any concern related to the type of wavelet filter used and to provide further robustness, we adopt three de-trending methods moving average, Hodrick-Prescott and Hamilton filter. Figure 38 shows the results. The left panels plot the dividend returns, $\frac{d_t}{q_t}$ where d_t is the dividend and q_t is the equity price, and the right panels plot the overall equity return including the capital gain, $r_t^e = \frac{d_t+q_{t+1}}{q_t}$. There is a tendency of the dividend return to rise and a slight increase in the overall equity returns. Jointly this may indicate a decline in the current equity price relatively to future valuations.

C.3. Nationality Re-assignment

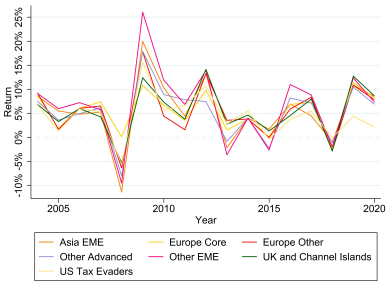
Table 13 shows the nationality re-assignment of equities and corporate bonds for 2020 in millions of dollars and for the top 6 countries in corporate and the top 7 in equities.

C.4. Regional Portfolio Returns for Corporate Bonds.

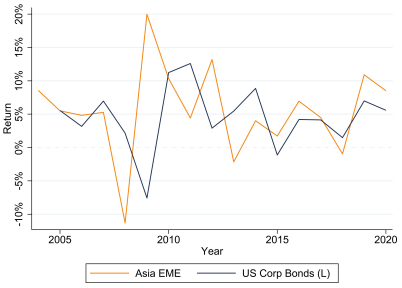
Figures 40 and 41 plot the corporate bond returns on U.S. and foreign firms, for different regions, based on residence and nationality of the security.

Figures 42 shows results for sovereign bonds and focusing on some of the regions,[38] while 41 in Appendix C plots the same for corporate bonds. Bond returns are generally higher, even more so in the last part of the sample, in all European countries, Asia and Latin America. This confirm the classical convenience yield for U.S. bonds, more so for sovereign.

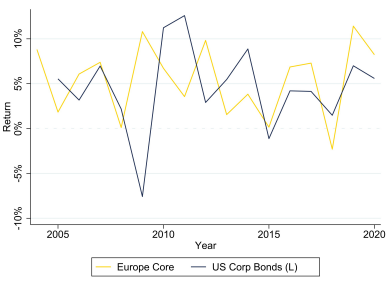
Figure 40: **The figure compares the returns, computed using the security-based method, on US claims to foreign corporate bonds across the following regions Asia, Core Europe, Emerging Markets, U.K. and Caribbean and financial centers. Returns are compared to returns earned by foreign on corporate bonds issued by U.S. firms. Securities are assigned based to countries based on firm nationality. The time period is 2004-2020. Country list in geographical regions is defined in the main text.**



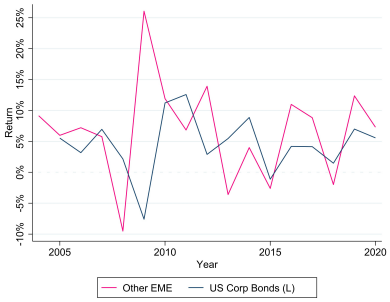
All Foreign and US



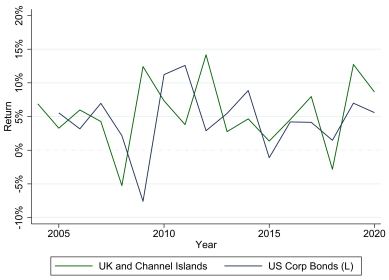
Asia vs US



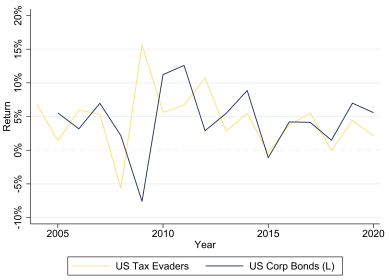
Core Europe vs US



Emerging Economies vs US



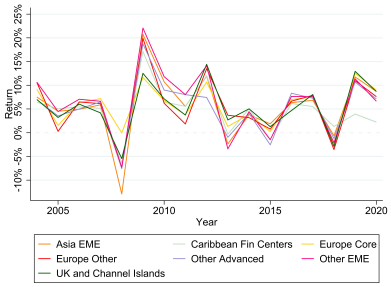
UK and Channel Islands vs US



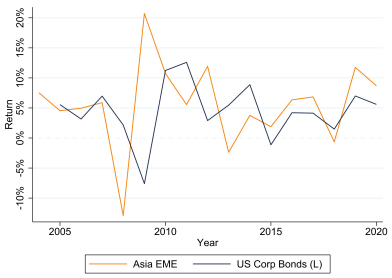
US Non-resident vs US

38 Note that for sovereign there is no difference between the nationality and residence of issuers. The difference is relevant for corporate bonds and equities.

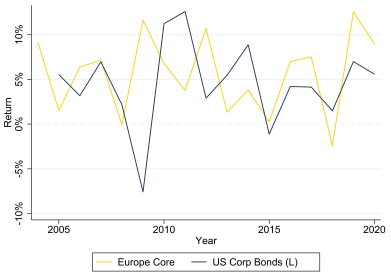
Figure 41: **The figure compares the returns, computed using the security-based method, on US claims to foreign corporate bonds across the following regions Asia, Core Europe, Emerging Markets, U.K. and Caribbean and financial centers. Returns are compared to returns earned by foreign on corporate bonds issued by U.S. firms. Securities are assigned based to countries based on firm residence. The time period is 2004-2020. Country list in geographical regions is defined in the main text.**



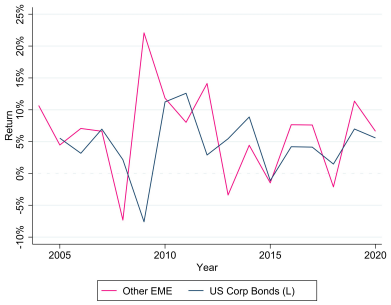
All Foreign and US



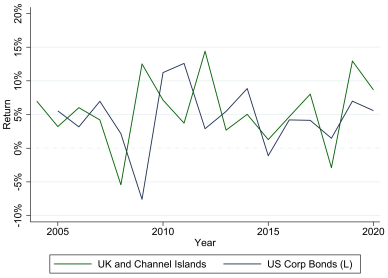
Asia vs US



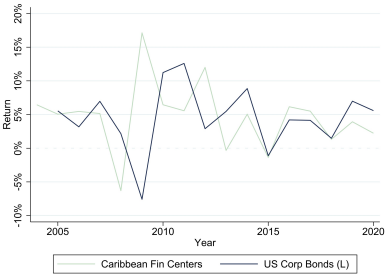
Core Europe vs US



Emerging Economies vs US

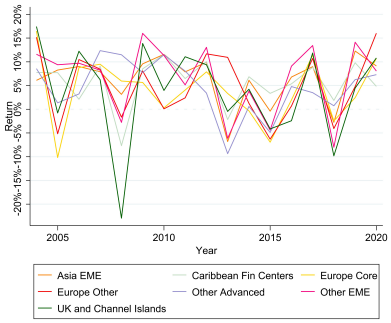


UK and Channel Islands vs US

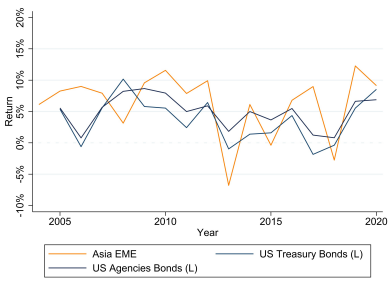


Caribbean Financial Centers vs US

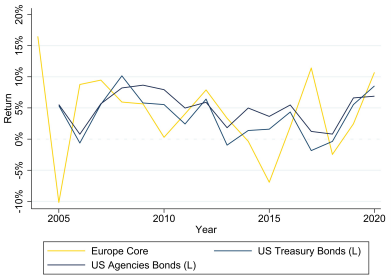
Figure 42: **The figure compares the returns, computed using the security-based method, on US claims to foreign sovereign across the following regions Asia, Core Europe, Emerging Markets, U.K. and Caribbean and financial centers. Returns are compared to returns earned by foreign on U.S. sovereign debt. The time period is 2004-2020. Country list in geographical regions is defined in the main text.**



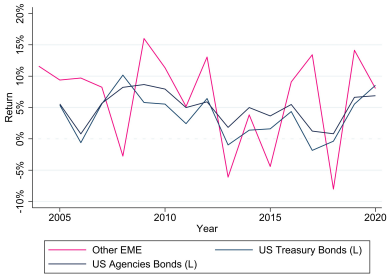
All Foreign and US



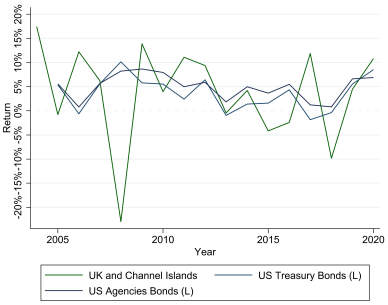
Asia vs US



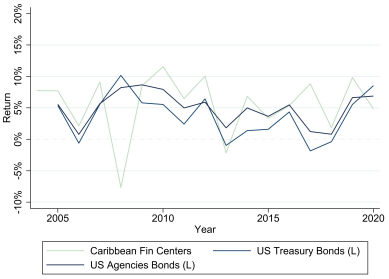
Core Europe vs US



Emerging Economies vs US

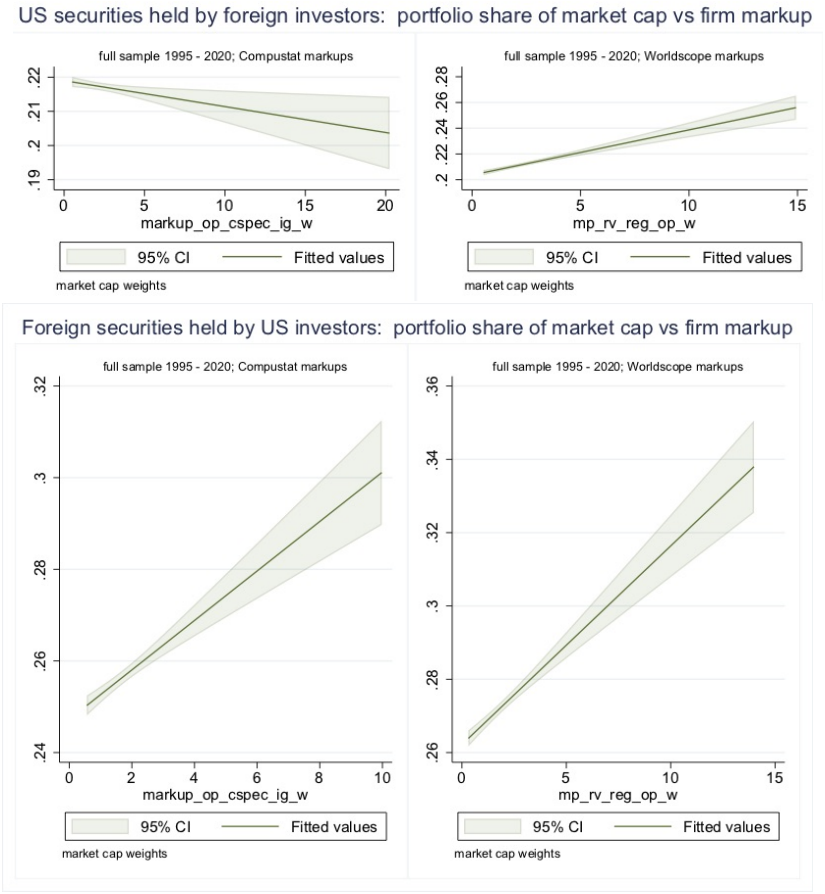


UK, Channel Islands vs US



Caribbean Fin Centers vs US

Figure 43: **Figure 43 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities in the TIC dataset with the firm mark-ups estimated through for all U.S. (top panels) and foreign (bottom panels) firms in Worldscope. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.**

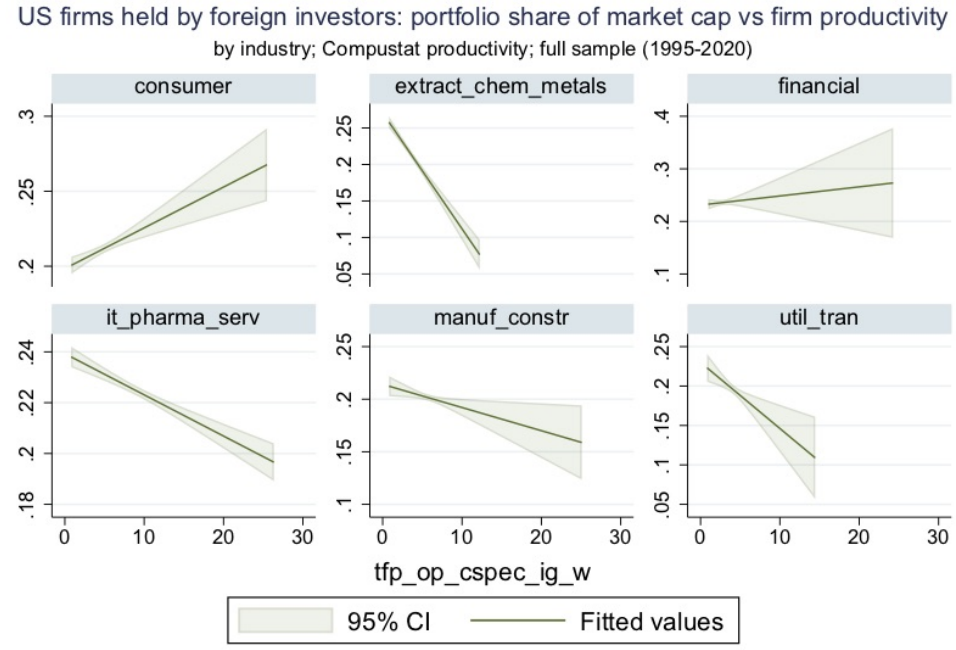


C.5. Additional Results on Correlation of Equity Shares with Firm Measures

Equity Shares and Mark-ups. Figure 43 shows the correlations between equity portfolio shares at security level and the mark-ups estimated with Worldscope data on the full sample of firms. The plot complements 45 that shows the same correlations using Compustat data. Correlations are positive only for foreign firms. Hence claims are allocated to best performers, while liabilities are not. Note that contrary to the figure 45 in the main text the current plot includes financial firms. This may suggest that foreign equity flows toward U.S. firms do not seem to improve allocative efficiency when financial firms are included in the sample.

Correlations Equity Shares with Productivity. Figure 44 shows the correlation for U.S. firms and foreign firms in the TIC dataset between portfolio shares and firm productivity, measured with Olley and Pakes (1996).

Figure 44: **Figure 44 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. liabilities and claims in the TIC dataset with the productivity (Olley and Pakes (1996)) of the issuing firm estimated through Compustat data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020 for U.S. firms and 2005-2020 for foreign firms. Green bands are 95% confidence intervals.**



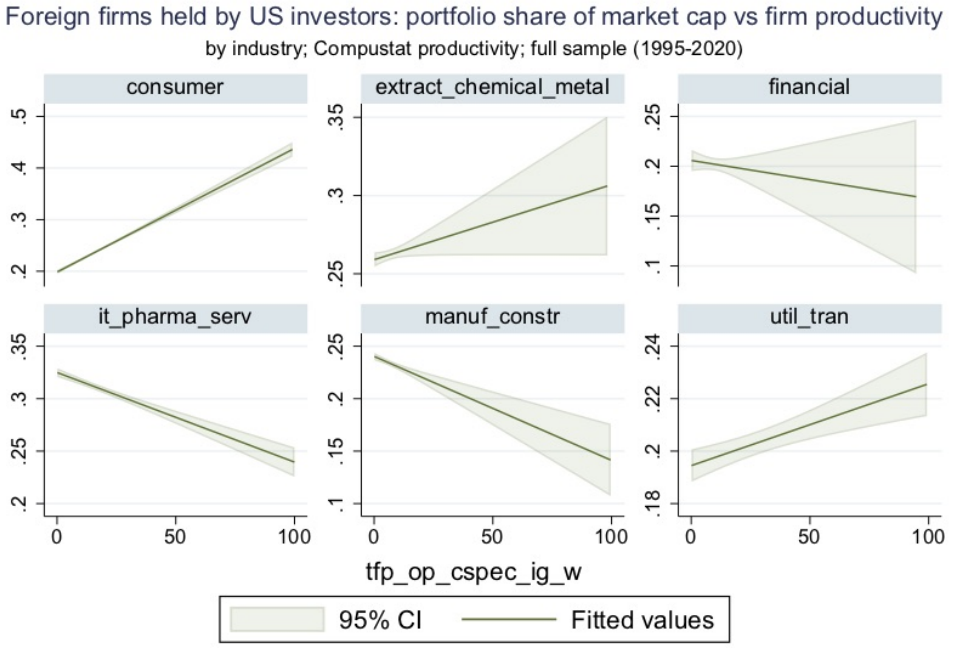
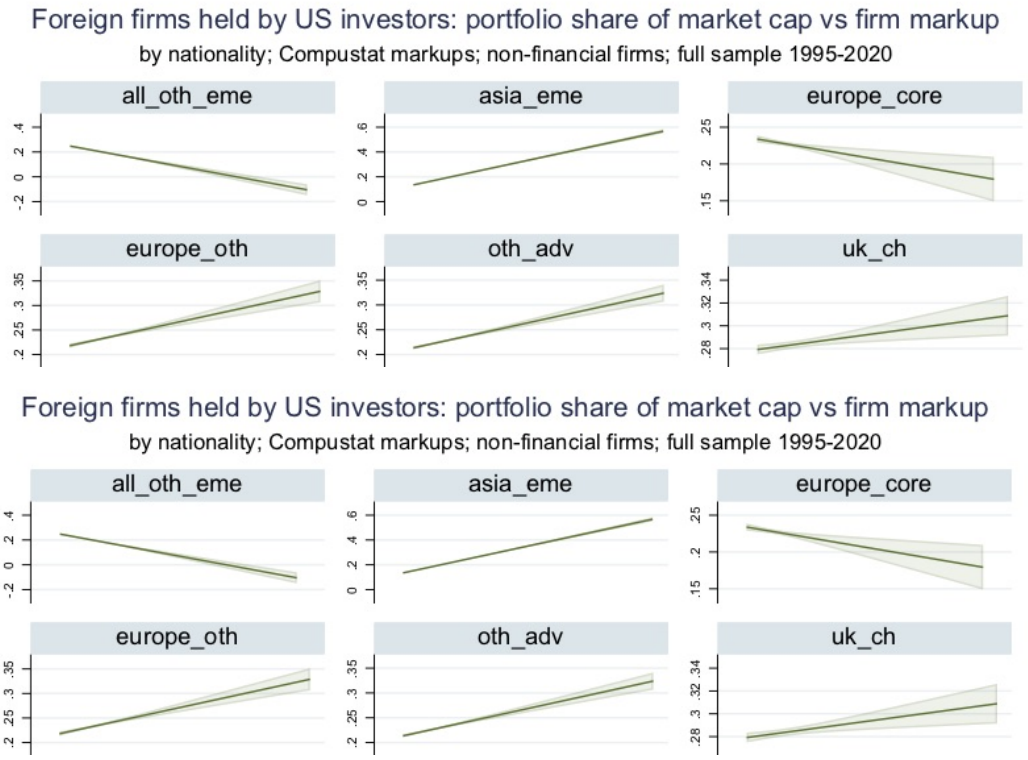


Figure 45: **Figure 45 plots the correlation of the equity share minus the market capitalization of firm i, for securities of U.S. claims in the TIC dataset with the firm mark-ups estimated through both Compustat and Worldscope data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 1995-2020. Green bands are 95% confidence intervals.**



Regional break-down for correlations equity shares and mark-ups. Figure 45 shows the correlation of net equity shares with mark-ups, which is positive mostly for Asian and European firms.

C.6. Correlations Equity Shares with Probability and Distance to Default by Sector.

Certain sectors are more likely to exposed to risks than others and hence they may receive less funding that it would be desirable. Figure 46 shows correlations of the equity shares, netted out of market capitalization, over the probability of default across sectors and for U.S. (top panel) and foreign firms (bottom panel). Figure 47 shows the correlations of equity shares and distance to default broken down across sectors. The correlations are all positive for U.S. firms and tend to be mostly negative for foreign firms. This is likely due to differences in the composition of firm across countries. The probability of default of U.S. firms indeed tends to exhibit longer right tails (see figure 48). This higher tolerance for risk is likely due to

the more efficient repossession guaranteed by the financial institutions or the legal system. Larger probability of default for certain sectors is also linked to the structural characteristics of the production process. Based on those observations in the regressions between portfolio shares and distance to default, shown in the main text, we net our the latter by its mean per country. This netting allows us to purge for composition effects.

Figure 46: **Figure 46 plots the correlation broken down by sector of the equity share minus the market capitalization of firm i, for the securities of U.S. claims and liabilities in the TIC dataset with the probability of default, measured using Refintiv data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 2005-2020. Green bands are 95% confidence intervals.**

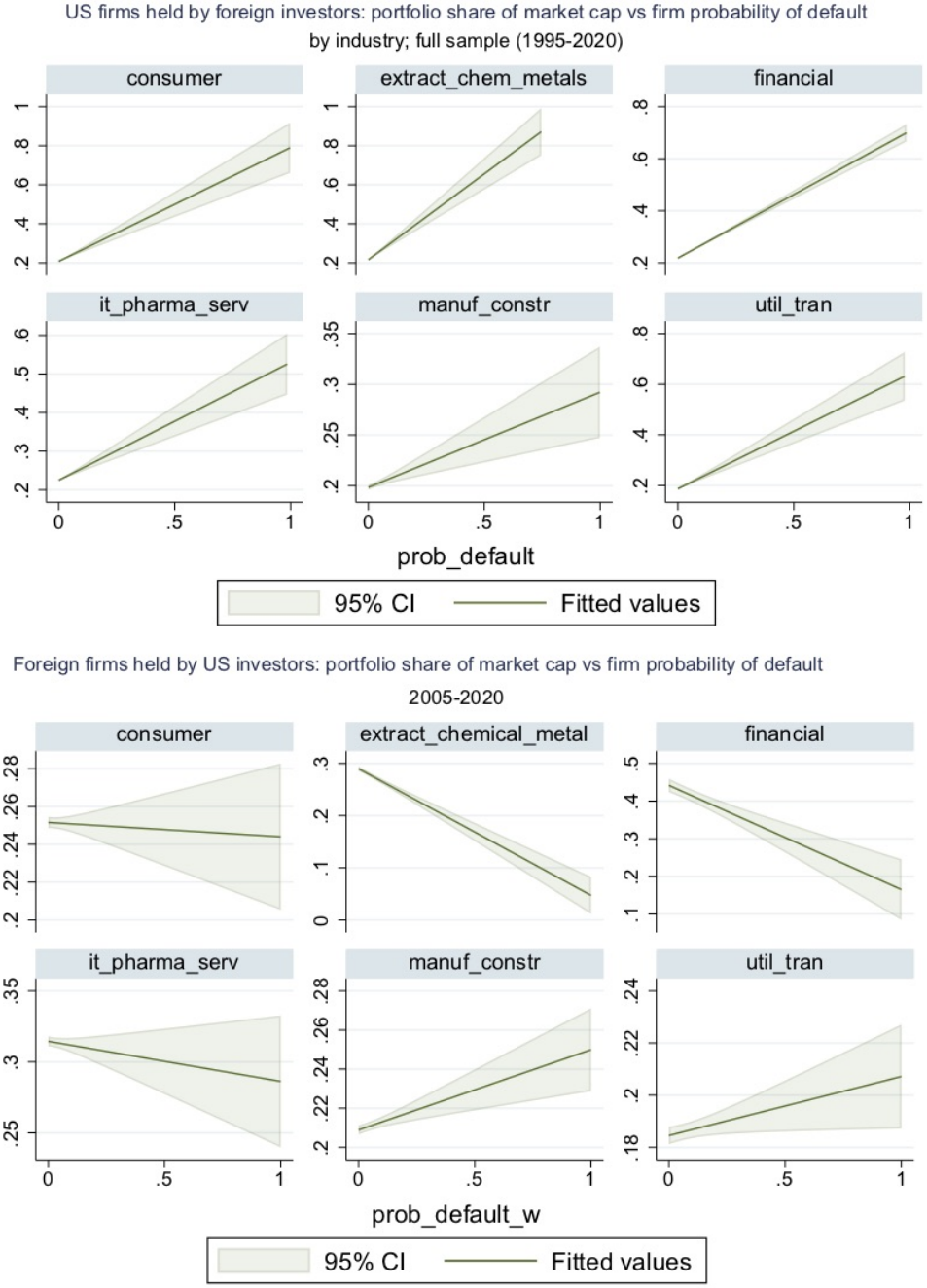


Figure 47: **Figure 47 plots the correlation broken down by sector of the equity share minus the market capitalization of firm i, for the securities of U.S. claims and liabilities in the TIC dataset with firm distance to default measured using from Refinitiv data. The cross-sectional regression is estimated using the cross sectional averages on the time sample 2005-2020. Green bands are 95% confidence intervals.**

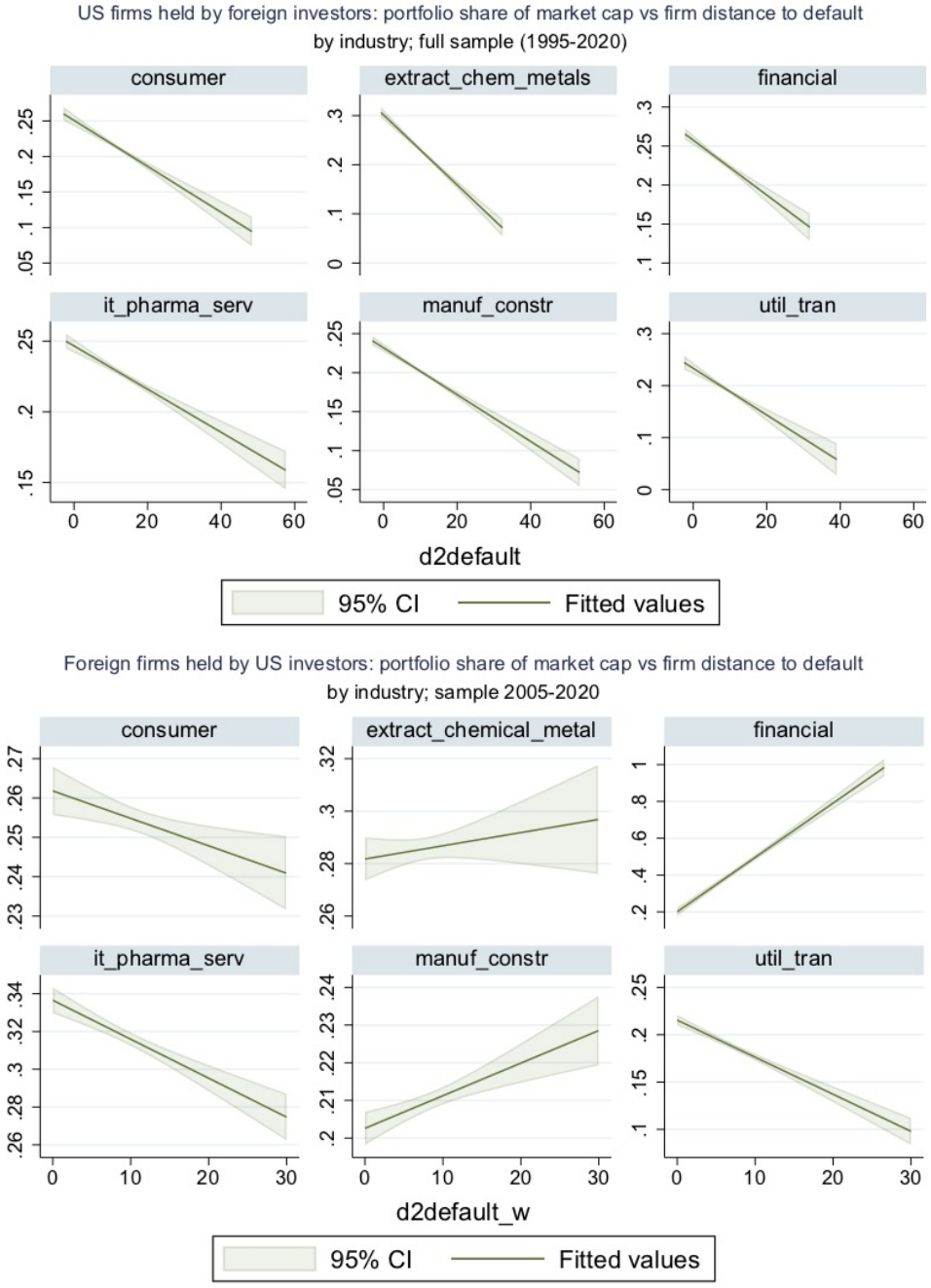


Table 11: **Average returns and differentials by asset type from 2005-2020. Residence Basis. See Table 1 for definitions.**

Security-Level	2005-2010	2011-2014	2015-2020	Total
Equity return claims	10.43	6.42	10.13	9.32
Equity return liabilities	2.88	18.35	10.80	9.71
Bond return claims	5.26	4.51	4.26	4.70
Bond return liabilities	4.65	4.28	3.29	4.05
Total return claims	8.84	5.67	8.63	7.97
Total return liabilities	4.08	8.90	6.29	6.11
Total return differential	4.17	-2.14	1.97	1.77
Index	**2005-2009**	**2010-2014**	**2015-2020**	**Total**
Equity return claims	11.67	6.09	8.76	9.18
Equity return liabilities	1.99	20.55	10.33	9.76
Bond return claims	5.77	3.89	3.60	4.49
Bond return liabilities	5.15	3.10	3.29	3.94
Total return claims	9.79	5.28	7.43	7.78
Total return liabilities	4.15	8.82	6.10	6.05
Total return differential	5.17	-2.5	1.01	1.68
BEA	**2005-2009**	**2010-2014**	**2015-2020**	**Total**
Equity return claims	9.58	6.10	8.43	8.28
Equity return liabilities	3.85	12.64	10.73	8.63
Bond return claims	5.51	5.45	6.40	5.83
Bond return liabilities	4.47	3.24	3.45	3.78
Total return claims	8.54	5.89	7.93	7.65
Total return liabilities	4.35	6.84	6.60	5.82
Total return differential	4.19	-0.94	1.33	1.83

Table 12: De-trended returns for claims and liabilities by asset class and return method. See Table 1 for definitions. Two different trending methods are used: Hodrick-Prescott with smoothing parameter based on Ravn and Uhlig (2002) and Hamilton (2018) method.

	Security-Level	Index	BEA ret	BEA raw
Equity Claims HP	9.32	9.37	8.19	9.54
Equity Liabilities HP	9.71	9.68	8.76	9.81
Equity Claims Hamilton	6.47	8.44	7.43	9.33
Equity Liabilities Hamilton	9.13	8.74	8.55	8.72
Bond Claims HP	4.73	5.05	6.00	7.32
Bond Liabilities HP	4.05	3.96	3.86	4.01
Bond Claims Hamilton	5.04	6.01	6.12	8.78
Bond Liabilities Hamilton	4.15	4.65	3.96	3.97

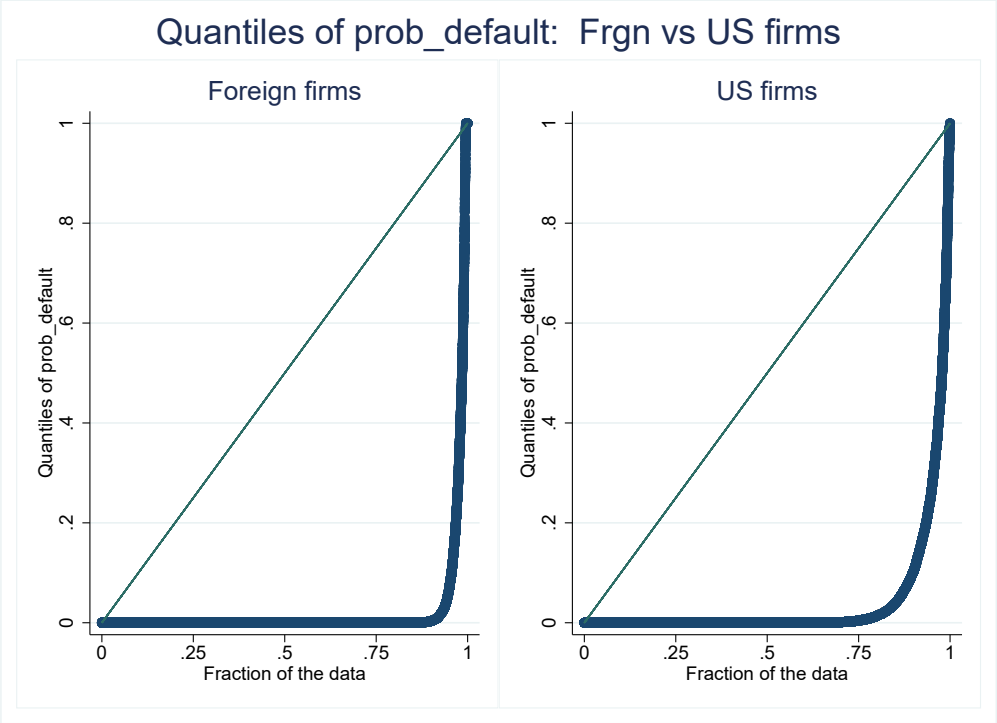
Table 13: List of top countries based on nationality reassignment of equities and bonds for 2020. Units are million of dollars

Top countries	Equity reassignment	Top countries	Bonds reassignment
United States	995618	United States	529363
China	766978	China	34040
France	48849	Brazil	26944
Italy	33398	Switzerland	24143
Sweden	30036	Germany	23317
Hong Kong	40954	U. K.	23065
Brazil	23413		

Table 14: **Kolmogrov Smirnov tests for equality of mark-up distributions over two sample periods, 2004-2009 and 2014-2019. Tests conducted for distribution of mark-ups computed with Olley and Pakes (1996) over firms in different sectors. Left columns are for U.S. firms and right columns for foreign firms.**

	U.S. Firms			Foreign Firms		
	Time period	Den	p-values	Time period	Den	p-values
Financial	2004-09	0,3685	0	2004-09	0,2101	0
	2014-19	-0,0036	0,981	2014-19	-0,0317	0,765
	Combined	0,3685	0	Combined	0,2101	0
Oil, gas, mining, metals	2004-09	0,0208	0,716	2004-09	0,0072	0,923
	2014-19	-0,0618	0,052	2014-19	-0,0422	0,065
	Combined	0,0618	0,105	Combined	0,0422	0,129
IT, electronics, pharma	2004-09	0,0275	0,067	2004-09	0,086	0
	2014-19	-0,0337	0,017	2014-19	-0,0067	0,901
	Combined	0,0337	0,034	Combined	0,086	0
Utilities, transportation	2004-09	0,0545	0,33	2004-09	0,0171	0,784
	2014-19	-0,1087	0,012	2014-19	-0,0681	0,021
	Combined	0,1087	0,024	Combined	0,0681	0,041
Manufacturing, construction	2004-09	0,1226	0	2004-09	0,036	0,03
	2014-19	-0,0012	0,998	2014-19	-0,0154	0,526
	Combined	0,1226	0	Combined	0,036	0,061
Consumer	2004-09	0,026	0,424	2004-09	0,0691	0
	2014-19	-0,0563	0,018	2014-19	-0,0034	0,978
	Combined	0,0563	0,036	Combined	0,0691	0
All industries	2004-09	0,0721	0	2004-09	0,0465	0
	2014-19	-0,0122	0,274	2014-19	-0,0048	0,797
	Combined	0,0721	0	Combined	0,0465	0

Figure 48: **Figure 48 compares distribution of probability of default for U.S. and foreign firms matched with TIC securities. Sample period 2005-2020.**



Distribution of Probability of Default for U.S. and Foreign

C.6.1. Global Compustat versus Worldscope

As noted earlier we have used the firm accounting data from Global Compustat as our benchmark since the overlap with the TIC securities is larger. Throughout the draft we have provided a comparison of our results across the two databases. They were largely robust across the two databases except in few instances in which the selection of firms, different across the two databases, would affect correlations in specific sectors.

In here we provide a further assessment of the comparison between the two databases. Specifically we plot the kernel density for one of the firm measures, namely mark-ups, for the samples of firms in the two databases across two different sample periods. The density is broadly similar in each of the two time sample and for both sample of firms it shifts forward in the second sample.

Figure 49: **Figure 49 compares kernel densities of mark-ups in the securities of U.S. claims and liabilities when matched with firm measures computed either through Compustat or through Worldscope.**

