



**Center for Analytical Finance  
University of California, Santa Cruz**

**Working Paper No. 47**

**Industry-Level Home Bias**

Chenyue Hu

University of California, Santa Cruz

October 25, 2017

**Abstract**

This paper examines the home bias phenomenon in international finance at the industry level. Using unique financial datasets, I calculate the sectoral home bias of 27 industries in 43 countries. The empirical findings include: (1) home bias is stronger when and where capital restrictions are greater, (2) nontradable sectors exhibit stronger home bias, and (3) home bias decreases in sectoral productivity, suggesting that investors show a stronger preference for domestic assets of less productive sectors. To rationalize this empirical finding, I build a model with a multi-sectoral setting to shed light on the implications of industrial structure for international portfolio choice.

**About CAFIN**

The Center for Analytical Finance (CAFIN) includes a global network of researchers whose aim is to produce cutting edge research with practical applications in the area of finance and financial markets. CAFIN focuses primarily on three critical areas:

- Market Design
- Systemic Risk
- Financial Access

Seed funding for CAFIN has been provided by the Division of Social Sciences at the University of California, Santa Cruz.

# Industry-Level Home Bias

Chenyue Hu

*University of California, Santa Cruz*

October 25, 2017

## **Abstract**

This paper examines the home bias phenomenon in international finance at the industry level. Using unique financial datasets, I calculate the sectoral home bias of 27 industries in 43 countries. The empirical findings include: (1) home bias is stronger when and where capital restrictions are greater, (2) nontradable sectors exhibit stronger home bias, and (3) home bias decreases in sectoral productivity, suggesting that investors show a stronger preference for domestic assets of less productive sectors. To rationalize this empirical finding, I build a model with a multi-sectoral setting to shed light on the implications of industrial structure for international portfolio choice.

---

Email: [chu78@ucsc.edu](mailto:chu78@ucsc.edu). I would like to thank Kathryn Dominguez, Stefan Nagel, Alan Deardorff, Javier Cravino, and Linda Tesar for comments and support. All mistakes are mine.

# 1 Introduction

A well-established fact in international finance is that investors exhibit strong bias in favor of domestic equities, despite the current integration of global financial markets. Contradicting the traditional finance theory that investors can reap substantial benefits from international portfolio diversification, the phenomenon of “equity home bias” continues to draw active interest from economists.

A large body of literature has focused on home bias at the national level, but little is known at the industry level about investors’ preference between domestic and foreign assets. Using Factset/Lionshare, a unique dataset on institutional investors’ equity holdings, complemented by information on market capitalization from Datastream, I compute the sectoral home bias of 27 industries in 43 countries. I then document empirical regularities in sectoral home bias by evaluating country, sector, and time effects respectively. These results at the industry level enable me to examine various determinants of equity home bias in unprecedented detail.

In the literature there are two broad classes of explanations for home bias: international market frictions and risks-hedging by investors. The first strand of literature focuses on institutional transaction barriers and informational frictions in global financial markets as an explanation for why investors tilt their portfolios toward domestic securities.<sup>1</sup> The second strand of literature studies the correlation between asset returns and country-specific factors, including non-diversifiable labor income and consumption in influencing investors’ choice between domestic and foreign equities. The resulting portfolios are optimal, which is different from the case when market distortions stemming from institutional and informational costs are the reason for home bias.

In this paper, I empirically find that home bias is stronger where and when capital restrictions are greater by conducting both cross-sectional and time-series analyses. Cross-sectionally, OECD countries, which are less subject to capital restrictions, on average show sectoral home bias that is 0.5 standard deviations lower than the bias in non-OECD countries. This finding suggests that countries with fewer institutional barriers exhibit greater international diversification. The result is robust when considering the Chinn-Ito index instead of the OECD dummy as a measure of capital account openness.<sup>2</sup>

---

<sup>1</sup>Investors’ behavioral biases driven by these market frictions can also be counted in this category. See [Stulz \(1995\)](#), [Lewis \(2011\)](#), and [Coeurdacier and Rey \(2013\)](#) for surveys of the papers that use market frictions to rationalize home bias.

<sup>2</sup>The Chinn-Ito index is a widely-used measure of capital restrictions in international finance. It is coded with the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Over time, sectoral home bias has fallen by 0.014 standard deviations annually since 2005. This decline trend in home bias can be attributed to the use of electronic trading and increasing exchanges of information across borders, both of which have significantly reduced international market frictions. Moreover, I find that the decline is especially pronounced for OECD countries, suggesting that financial integration has been driven mainly by foreign investments of developed economies rather than by market liberalizations in emerging markets. These sectoral findings, complementing national findings in [Coeurdacier and Rey \(2013\)](#) and [Lane and Milesi-Ferretti \(2003\)](#), indicate that market frictions in global financial markets constrain international diversification.

Furthermore, I use sectoral home bias to examine investors' motives for risk-hedging. To hedge against fluctuations in purchasing power, risk-averse investors hold assets whose returns increase in consumption at home. Previous work, including [Obstfeld and Rogoff \(2001\)](#), suggests that returns to nontradable sectors are positively correlated with domestic price and consumption levels. This positive correlation prompts investors to hold domestic assets, particularly domestic nontradable sector assets.<sup>3</sup> However, no sectoral information on home bias was available to test the hypothesis that home bias is stronger in nontradable sectors than in tradable sectors. This paper is able to address this literature gap with industry-level data. My empirical results confirm the hypothesis: home bias is 0.2 standard deviations lower in tradable sectors than in nontradable sectors. Over time, a tradable sector experiences a greater decline in sectoral home bias than a nontradable sector, indicating that home bias in nontradable sectors is more rigid and does not decrease as much as tradable sectors with reductions in financial market frictions. This empirical finding corroborates the theoretical arguments made by [Tesar \(1993\)](#) and [Obstfeld and Rogoff \(2001\)](#) that nontradable sectors can potentially induce home bias at the country level.

Labor income risk is another factor that influences investors' portfolio choices. Non-diversifiable labor income tilts optimal portfolios toward foreign assets since it is positively correlated with domestic capital income. If investors hold only domestic assets, both labor income and financial income plummet when the domestic economy collapses. The international diversification puzzle is deepened once the implications of labor income for portfolio composition are taken into account, as is argued by [Baxter and Jermann \(1997\)](#). This reasoning also applies to the analysis of sectoral home bias. A sector with greater productivity is exposed to more risks because the country's labor income is more high-

---

<sup>3</sup>Nontradable sectors typically include services, construction, and utilities; while tradable sectors include manufacturing and transportation.

ly correlated with the returns to that sector than with the returns to a less productive sector. Since productive sectors tend to hire more labor and export more goods, they have a greater impact on the aggregate economy such that the whole country experiences drastic income loss when key industries fail. Therefore, to hedge against labor income fluctuations, investors hold fewer home assets in more productive sectors and hence show weaker sectoral home bias. This explains why sectoral productivity can be an important determinant of sectoral home bias. To empirically test this hypothesis, I use the UNIDO Industrial Statistics Database to estimate sectoral total factor productivity (TFP).<sup>4</sup> I use three methods to do the calculation. After that, I confirm the hypothesis by establishing an empirical finding that sectoral home bias decreases in sectoral productivity. When country, sector, and time fixed effects are controlled for, a 1 percent increase in sectoral TFP is associated with a 0.001 standard-deviation decrease in sectoral home bias. To attribute this finding to risk-hedging, I further empirically verify that a country's labor income is more highly correlated with the returns to sectors with greater productivity.

In the theoretical part, I build a two-country, two-sector model to explain why sectoral productivity influences sectoral home bias. Suited for the industry-level analysis, this framework departs from previous theoretical work in the home bias literature that assumes a single sector in each country. I solve the endogenous portfolio choice problem using the perturbation method developed by [Devereux and Sutherland \(2007\)](#). They employ a higher degree of approximation of an investors' objective function to capture lower-order portfolio behavior. The solution to the optimal portfolio choice problem, capturing correlations between asset returns and country-specific labor income, reflects investors' risk-hedging motives. The numerical results of the model, consistent with my empirical findings, suggest that investors show weaker sectoral home bias for more productive sectors in their countries.

My empirical and theoretical results complement existing studies of home bias by adding the sectoral dimension. [Coerdacier and Rey \(2013\)](#) provide a critical survey of the literature on home bias. Comprehensive empirical studies are relatively scarce due to the lack of data on national home bias, let alone sectoral home bias. Using unique financial datasets, this paper compiles a comprehensive and detailed home bias index. Using the index, I document empirical regularities not found in previous work that allow me to explore the determinants of home bias.

These new findings about sectoral home bias and productivity underscore the need

---

<sup>4</sup>The UNIDO Industrial Statistics Database reports sectoral data on value-added, employment, wages, and fixed capital formation.

for a new model that links industrial structure to portfolio choice. Unlike previous theoretical papers that treat a country as a whole, such as [Heathcote and Perri \(2013\)](#) and [Cole and Obstfeld \(1991\)](#), my model allows for multiple sectors within countries and intra-sectoral trade across countries. Investors choose assets based both on the country of issue and on the sector, and thus have more ways to hedge risks. My model is also a more general case of [Tesar \(1993\)](#) and [Matsumoto \(2007\)](#), who assume one tradable and one nontradable sector in each country. I introduce sector-specific trade costs to capture the nontradability of some industries.

The remainder of the paper proceeds as follows: Section 2 describes the data and methods of construction for sectoral home bias. Section 3 presents empirical regularities of sectoral home bias by analyzing country, sector, time, and especially, productivity effects. Section 4 builds and solves a two-country two-sector model to explain the effect of sectoral productivity on home bias. Section 5 concludes.

## 2 Constructing the Sectoral Home Bias Index

In this section, I describe the data source and the method to construct the sectoral home bias index.

[Coerdacier and Rey \(2013\)](#) use the difference between the country-level holdings of equities and the share of market capitalization in the global equity market to measure national home bias. This difference reflects the deviation of data from the basic International CAPM model. The model predicts that a representative investor should hold a world market portfolio, in which the share of his financial wealth invested in local equities equals the share of local equities in the world market.

I apply the same idea and method to the industry-level analysis in compiling the sectoral home bias index. Home bias in country  $i$  sector  $s$  at time  $t$  is equal to

$$HB_{i,s,t} = 1 - \frac{\text{Share of Sector } s \text{ Foreign Equities in Country } i \text{ Equity Holdings at time } t}{\text{Share of Sector } s \text{ Foreign Equities the World Market Portfolio at time } t} \quad (1)$$

The numerator in the expression for  $HB_{i,s,t}$  uses data from Factset/Lionshare, while the denominator uses market values from Datastream to get a country's equity share in industry  $s$ .

Factset/Lionshare provides comprehensive data on the equity holdings of institutional investors from more than 100 countries or regions since 1998. Typical institutional

investors include banks, insurance companies, retirement or pension funds, hedge funds and sovereign wealth funds. Table A.1 lists the top 20 U.S. institutional investors by assets as of 2014Q3.

I use institutional investors' holdings as a proxy for the whole country's portfolio choice for the following reasons. First, institutional investors have replaced households as the main player in equity markets worldwide. Figure A.2 shows how the U.S. household share of equity ownership has fallen significantly over time. Robert Shiller calls this phenomenon the "migration of capital from Main Street to Wall Street". The dominance of institutional investors over household investors is also commonly observed in other countries.<sup>5</sup> Second, the national home bias index constructed with the Factset/Lionshare data lines up well with the index constructed by Coeurdacier and Rey (2013) who use the IMF CPIS data encompassing countries' aggregate equity positions (see A.3). This consistency shows that under-representation caused by considering only institutional investors is not a big concern. Third, for practical reasons, information on household portfolio is scarce, leaving institutional investors as the only subject whose portfolio distribution across sectors and countries can be studied. The Factset/Lionshare data originate from public filings by institutional investors (such as 13-F filings with the Securities and Exchange Commission in the U.S.), regulatory agencies around the world, and company annual reports; such information is not available for households. Last, Table A.1 shows that the top U.S. institutional investors are the big organizations that U.S. households typically go to for portfolio management. Hence these institutions' portfolio choices are representative of households' choices to a great extent.

Given the Factset/Lionshare data, I group securities by their location and sector, and I group holders by their nationality. Figure A.1 shows the funds allocation for the U.S. in January 2015. The U.S. invests 83.1 percent of its equities domestically. Given the fact that the U.S. market accounts for around 40 percent of the world market portfolio, this allocation indicates strong national home bias. In addition, U.S. investments are highly diversified sectorally, with finance, health, and electronics being the most popular ones.

Calculating sectoral home bias also requires information on market capitalization. Thomson Reuters Datastream offers global country- and sector-level financial data, including market values. Factset/Lionshare and Datastream unfortunately do not categorize industries in the same way, so I construct a concordance of the two classification systems (see Table A.2).

---

<sup>5</sup>For instance, institutions accounted for 88 percent of the ownership of EU corporate equities in 2012, according to the INSEAD OEE Data Services.

Combining all the data together, I compile the annual sectoral home bias index using Formula 1. The index covers 27 sectors in 43 countries. Time averages between 1998 and 2014 for home bias of country  $i$  sector  $s$  (denoted as  $\bar{H}B_{i,s}$ ) are listed in Tables A.4 - A.6.  $\bar{H}B_{i,s} = 1$  indicates that country  $i$  is fully home biased in sector  $s$  since it does not hold any foreign equities.  $\bar{H}B_{i,s} = 0$  indicates that country  $i$  is fully diversified. In theory,  $\bar{H}B_{i,s}$  can take any value equal to or smaller than 1 (including negative values). When the value is negative, it means that the country is over-investing in foreign equities relative to market shares for the sector.

Figure 1 shows the histogram of sectoral home bias  $\bar{H}B_{i,s}$ . There are 834 observations in total, with mean 0.42 and standard deviation 0.36. The index ranges from -0.2 to 1, with many observations clustered around 0 and 1, representing the case with no home bias and full home bias respectively. The mean value 0.42 suggests that the share of foreign equities in investors' portfolios is about 60 percent of what it should be based on the International CAPM.

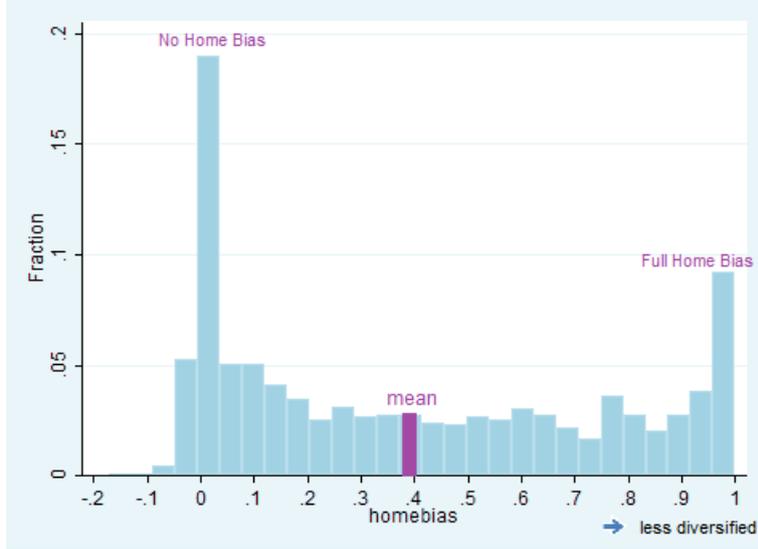
Figure 2 plots the U.S. sectoral home bias. The mean value is 0.65 and standard deviation is 0.20. Furnishings, apparel, and utilities show the strongest home bias. Real estate, publishing, automobiles, and telecommunications show the weakest. In particular, real estate is the only sector with negative home bias, indicating that U.S. investors hold more foreign real estate assets than their share in the world market.

As is shown in Tables A.4 - A.6, there is great variation in the degree to which investors prefer domestic equities across industries and countries. In the next section, I investigate various determinants of sectoral home bias to explore the factors that influence investors' portfolio choices in the global financial market.

### 3 Empirical Analysis

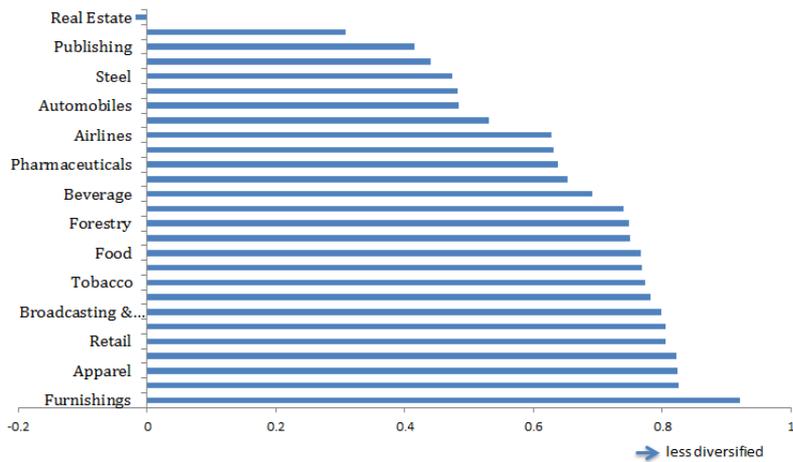
In this section, I explore the factors that drive the variations in sectoral home bias. In particular, I examine potential explanations for home bias, including institutional frictions and risk-hedging patterns. Sectoral home bias of industry  $s$  in country  $i$  at time  $t$  is influenced by country-, sector-, and time-specific factors, as well as their combined effects. I discuss each one in turn. After that, I establish a robust finding that sectoral home bias decreases in sectoral productivity.

Figure 1: Distribution of Sectoral Home Bias



Note: This chart is a histogram of the sectoral home bias index. The formula used to construct the index is  $HB_{i,s} = 1 - \text{Share of Sector } s \text{ Foreign Equities in Country } i \text{ Equity Holdings} / \text{Share of sector } s \text{ Foreign Equities the World Market Portfolio}$ . The data are from Factset/Lionshare and Datastream. The index covers 27 sectors in 43 countries. There are 834 observations in total, with mean 0.42 and std. dev. 0.36. Detailed information is provided in Table A.4.

Figure 2: U.S. Home Bias by Sector



Note: The mean US sectoral home bias is 0.65 and the std. dev. is 0.20. The original data can be found in Table A.4.

### 3.1 Country Effects

When economists explore the causes of national home bias, they list institutional frictions such as capital controls as important reasons that investors prefer domestic assets.<sup>6</sup> These country-level barriers that impair global financial mobility should also help explain home bias at the industry level.

To find the relationship between institutional frictions and sectoral home bias, I first regress time averages for sectoral home bias (denoted as  $\bar{H}B_{i,s}$ ) on a dummy for OECD countries, which exhibit greater integration with the world financial market under fewer exchange barriers than developing countries. As is shown in Column 1 of Table A.7, an OECD country on average shows 0.186 lower sectoral home bias (or 0.515 standard deviations) than a non-OECD country. The result is similar after controlling for sector fixed effects (see Column 2). To illustrate this finding, take the automobile industry as an example. Sectoral home bias for the automobile industry is 0.99 in China, which has a long tradition of capital controls, versus 0.12 in the United Kingdom, which is one of the most open financial markets in the world. This result that investors in developed countries hold a larger share of foreign assets at the industry level is consistent with the country-level observations documented in Coeurdacier and Rey (2013) and Lane and Milesi-Ferretti (2003).

I then use the Chinn-Ito index as another proxy for financial openness in the regression. Chinn and Ito (2006) use the IMF's categorical enumeration reported in the Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) to code the index. This de-jure measure of capital account openness is widely used in the international finance literature. When I use the index, I take the mean value for each country over the same period that the home bias index covers. Higher values indicate less capital restrictions for countries. Columns 3 and 4 of Table A.7 show that a 1 standard-deviation increase in capital account openness measured by Chinn-Ito is associated with a 0.55 standard-deviation decrease in sectoral home bias, similar to the coefficients on the OECD dummy. The effect of countries' financial liberalization on sectoral home bias is hence robust under alternative specifications.

To sum up, variation in sectoral home bias decreases with countries' financial openness. These findings quantitatively support economists' views that institutional frictions in global equity markets impede international diversification.

---

<sup>6</sup>See, for instance, French and Poterba (1991), Stulz (1981) and Lewis (1999).

## 3.2 Sector Effects

Investors' motives to hedge against the risk arising from fluctuations in domestic consumption prices can explain equity home bias, as is argued by [Pesenti and Van Wincoop \(2002\)](#) and [Coeurdacier \(2009\)](#). If there are positive correlations between local prices and domestic asset returns, risk-averse investors have an incentive to hold home equities: when local goods become more expensive, they do not need to significantly compromise consumption since their shortfall in real income is offset, whether partially or fully, by their financial income.

If sectors are categorized into tradables and nontradables, hedging the risk requires that investors show higher degrees of home bias in the assets of nontradable sectors. In the case where tradable and nontradable consumption are log-separable in utility, [Obstfeld and Rogoff \(2001\)](#) contend that investors should hold globally diversified assets of tradable sectors and completely domestic assets of nontradable sectors. In doing so, investors insure themselves against all the fluctuations in expenditures on nontradables<sup>7</sup>.

While theoretical work is abundant, empirical work is missing as to whether investors show stronger home bias in nontradable sectors. This paper addresses this gap by analyzing home bias at the industry level. When categorizing industries into tradable and nontradable sectors, I follow the benchmark used by [Mano and Castillo \(2015\)](#), who classify industries' tradability based on the trade data. In [Table A.6](#), the industries coded 1-15 and 20-22 are tradable sectors, including manufacturing and transportation. Other industries are nontradable sectors, among which are construction, utilities, and services.

I regress sectoral home bias on a dummy for tradable sectors, and find that investors do exhibit weaker sectoral home bias in tradable industries. In [Column 1 of Table A.8](#), home bias in tradable sectors is lower than that in nontradable sectors by 0.151 standard deviations. After controlling for country fixed effects, the standardized coefficient becomes 0.197. In Spain, for example, sectoral home bias is 0.05 for chemicals but 0.82 for construction; there is a huge contrast between these tradable and nontradable sectors. This empirical result that home bias is stronger in the nontradable sector resonates with the theoretical arguments made by [Stockman and Dellas \(1989\)](#), [Obstfeld and Rogoff \(2001\)](#), and [Tesar and Werner \(1995\)](#), among others.

Another sector-specific variable that can potentially influence home bias through the risk-hedging channel is sectoral labor intensity. A more labor-intensive sector induces

---

<sup>7</sup>See [Coeurdacier and Rey \(2013\)](#) for a detailed list of papers that discuss the existence of nontradable sectors in explaining home bias.

employees in these sectors to hold more foreign assets to hedge against labor income risk. If these employees represent a significant share of a country’s investors, the country as a whole shows weaker sectoral home bias in more labor-intensive sectors. In Columns 3-4 of Table A.8, I include a measure of sectoral labor intensity constructed by Braun (2005) based on the ratio of the U.S. median industry mean wage to all manufacturing wages. In Column 3, I do not find noticeable a relationship between sectoral labor intensity and home bias.<sup>8</sup> In Column 4, when I control for country fixed effects I find the negative correlation is statistically significant at the 10 percent level. When labor intensity rises by 1 standard deviation, sectoral home bias decreases by 0.065 standard deviations. This finding can be explained by investors’ hedging against labor income risk.

To sum up, sectoral home bias decreases with the degree of sectoral tradability and labor intensity. These findings lend support to previous theoretical papers that focus on risk-hedging as an explanation for equity home bias.

### 3.3 Time Effects

National home bias has declined over the past several decades, as is documented by Coeurdacier and Rey (2013) and Lane and Milesi-Ferretti (2003). This pattern can be attributed to reductions in institutional frictions, transaction costs, and informational asymmetries. A decline in home bias is also observed at the industry level. When controlling for country and sector fixed effects, I find that sectoral home bias decreased by .04 standard deviations annually over the decade 2005 - 2014 (See Column 1 of Table A.9). After observing this general trend, I examine the sector and country characteristics that influence dynamic changes in sectoral home bias. To do so, I look at the coefficients on interaction terms between time and sector- or country-specific factors.

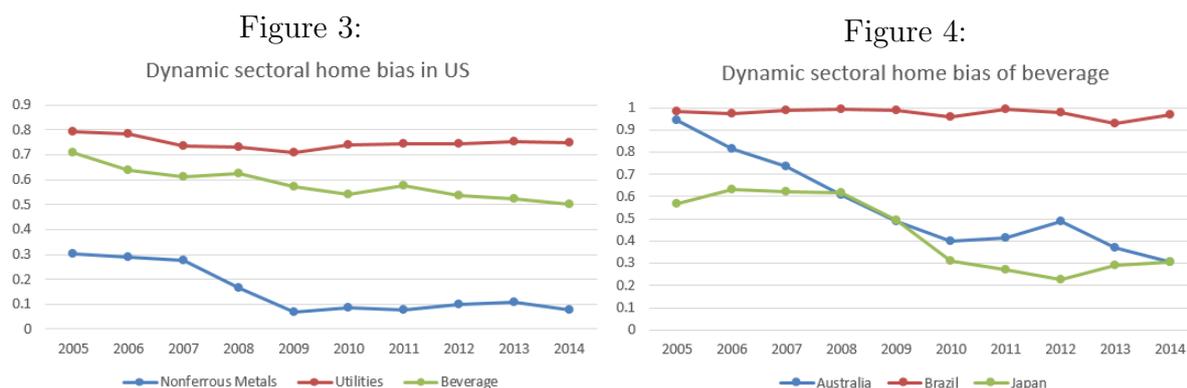
Column 2 of Table A.9 shows that home bias in a tradable sector decreases by 0.013 standard deviations more than home bias in a nontradable sector every year. This empirical observation is consistent with the theoretical argument made in the previous section on sector effects that home bias in nontradable sectors is strong and rigid due to investors’ risk-hedging. For example, Figure 3 plots the dynamic home bias of three sectors in the U.S. All the three industries have experienced declines in home bias. Among them, nonferrous metals and beverages show modest declines. Beverages decreased from 0.7 in

---

<sup>8</sup>The lack of obvious correlation can be driven by several factors, including limited sample size. Braun (2005)’s measure of labor intensity only covers 12 out of 24 sectors in my sample.

2005 to 0.3 in 2014, while nonferrous metals decreased from 0.3 to 0.1, which is close to the prediction of ICAPM (i.e., 0). Utilities, the only nontradable sector of the three, has had a stable home bias value of around 0.7 in recent years.

Column 3 of Table A.9 illustrates that an OECD country’s sectoral home bias decreases by 0.039 standard deviations more than that of a non-OECD country every year. This finding implies that the increase in international diversification has been driven mainly by developed economies’ foreign investment rather than by developing countries’ market liberalization. For instance, Figure 4 plots the dynamic home bias of the beverage industry in three countries over time. Australia shifted from full home bias (0.95) to weak home bias (0.3), while Japan’s home bias fell from 0.6 to 0.3. Brazil, the only developing economy of the three, had a constantly high degree of home bias (close to 1) over the decade.



Note: This figure presents dynamic sectoral home bias over the decade 2005-2014. The left graph plots the sectoral home bias of three industries in the U.S. The right graph plots the sectoral home bias of the beverage industries in three countries. They are used as examples to interpret the regression results in Table A.9 that examines sector and country characteristics which influence dynamic changes in sectoral home bias.

In a nutshell, sectoral home bias fell significantly over the decade. The decline was more pronounced for advanced economies with fewer institutional constraints as well as for tradable sectors for which there are fewer risk-hedging considerations and hence more diversification benefits.

### 3.4 Productivity Effects

Investors' portfolio choices are also influenced by the interaction among country, sector, and time factors. Among these factors, I hypothesize that sectoral productivity is a crucial determinant of sectoral home bias. The reasoning is as follows. The positive correlation between domestic labor income and financial income prompts investors to hold foreign assets to hedge against labor income risk. A sector with greater productivity is exposed to greater risk because the returns to that sector are more highly correlated with the country's labor income than is the case for the returns to a less productive sector. Since productive sectors tend to hire more labor and export more goods, they have a greater impact on the aggregate economy. When these sectors fail, the whole country suffers drastic income losses. Therefore, to hedge against labor income fluctuations, investors tend to hold fewer home assets in more productive sectors and hence show weaker sectoral home bias.

To quantitatively assess the correlation between productivity and home bias, I first use the UNIDO Industrial Statistics Database to calculate sectoral productivity. The dataset reports data at the 3- and 4-digit levels of ISIC Rev.4 on value -added, employment, wages, and fixed capital formation by sector. In addition to labor input, capital input is needed to calculate sectoral total factor productivity (TFP). Previous literature estimates capital stock using the perpetual inventory method (PIM) based on  $K_t = (1 - \delta)K_{t-1} + I_t$ , where  $K_t$  is the capital stock and  $I_t$  is the investment or fixed capital formation at time  $t$ .  $\delta$  represents capital depreciation, which is assumed to be 10 percent annually. To apply PIM, I need to compute the initial capital stock  $K_0$  of a sector. There have been multiple efforts in previous studies to calculate the national capital stock, and I apply them to the sectoral analysis. For instance, [Isaksson \(2007\)](#) argues that ten years of investment serves as an adequate proxy for the initial capital stock. Alternatively, [Harberger \(1988\)](#) proposes using the steady-state relationship derived from the Solow growth model:  $K_0 = \frac{I_0}{g+\delta}$ .  $I_0$  is investment in the beginning period and  $g$  is the average growth rate of investment. Moreover, [Inklaar and Timmer \(2013\)](#) argue that assuming an initial capital/output ratio  $k$  in  $K_0 = Y_0 \times k$  leads to superior results when they construct the Penn World Table. To employ this strategy, I compute the value of  $k$  by dividing the country's capital stock by its GDP (both in the initial period) with the data from the Penn World Table. The initial sectoral capital stock will be the product of the initial sectoral output and  $k$ .

After computing the initial capital stock of sector  $s$  in country  $i$  with the three meth-

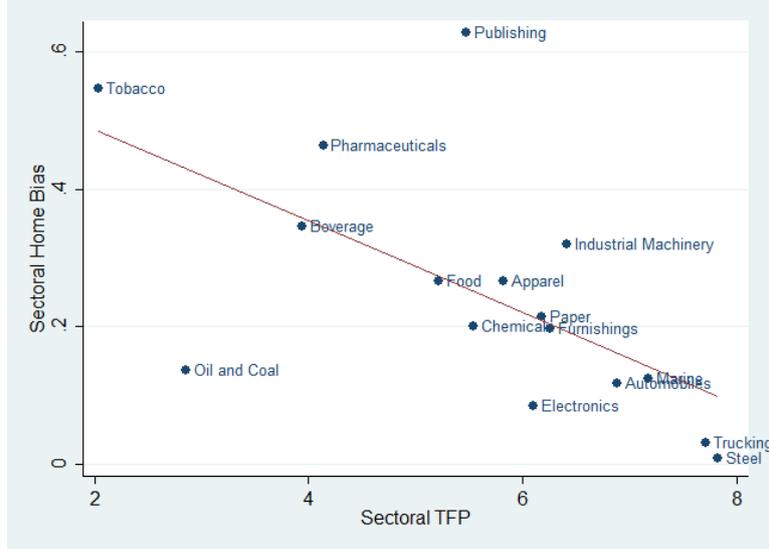
ods, I use  $K_{i,s,t} = (1 - \delta)K_{i,s,t-1} + I_{i,s,t}$  to trace the dynamic capital stock  $K_{i,s,t}$ . I also calculate sectoral factor intensity  $1 - \alpha_{i,s}$  by averaging the share of wages in value-added of a sector over time. Given all the information, sectoral total factor productivity is  $TFP_{i,s,t} = \frac{Y_{i,s,t}}{K_{i,s,t}^{\alpha_{i,s}} N_{i,s,t}^{1-\alpha_{i,s}}}$ , where  $Y_{i,s,t}$  is inflation-adjusted sectoral output and labor input  $N_{i,s,t}$  is the number of employees in that sector. In robustness checks (Table B.1), I also take into account differences in working hours and human capital across countries, and augment them in the denominator with  $\tilde{N}_{i,s,t} = N_{i,s,t} \times avh_{i,t} \times hc_{i,t}$ .

Table A.10 lists the regression results for sectoral home bias and sectoral TFP, with TFP measured in different ways.  $TFP_1$  uses Isaksson (2007)'s method,  $TFP_2$  uses Harberger (1988)'s, and  $TFP_3$  uses Inklaar and Timmer (2013)'s. In all the specifications, sectoral home bias decreases in sectoral productivity. For instance, Column 4 shows that, after controlling for country, sector, and time fixed effects, when sectoral TFP increases by 1 percent, sectoral home bias decreases by 0.001 standard deviations.

The United Kingdom provides a good illustration of the negative correlation between sectoral home bias and sectoral productivity. Figure 5 shows that U.K. investors have the strongest home bias in sectors with lower productivity such as beverages, tobacco, and pharmaceuticals, and the weakest home bias in sectors with higher productivity, including iron and steel, transports, and automobiles. This result confirms the hypothesis that home bias is weaker in more productive sectors than in less productive sectors.

To attribute the relationship between sectoral home bias and productivity to risk-hedging, I further investigate whether a country's labor income is more highly correlated with returns to the sectors with greater productivity. To this end, using national labor income data from Karabarbounis and Neiman (2013) and sectoral return data from Datastream, I calculate their correlation  $Corr(w_{i,t}L_{i,t}, r_{i,s,t})$ . After that, I test whether this correlation increases in a sector's average TFP over the years. As is shown in Table A.11, the correlation between national labor income and sectoral financial return is higher for sectors with greater productivity. Thus, investors have an incentive to hold more foreign assets in more productive sectors to hedge against labor income fluctuations. This risk-hedging mechanism can potentially explain the variation in sectoral home bias driven by productivity differences. In the next section, I build a model to elaborate on this mechanism.

Figure 5: U.K. Sectoral Home Bias and Sectoral Productivity



Note: This figure plots the relationship between sectoral home bias and sectoral TFP in the United Kingdom. I calculate the dynamic home bias and TFP (based on [Isaksson \(2007\)](#)'s method; in log) and averaged over time since 1998. There is a strong negative correlation between home bias and sectoral productivity.

## 4 Model

Motivated by the empirical analysis, I develop a theoretical model to elucidate the negative correlation between sectoral productivity and sectoral home bias. The mechanism of the model builds on the risk-hedging story mentioned earlier: a higher correlation between the performance of productive sectors and national labor income prompts investors to hold more foreign assets in those sectors.

In order to illustrate how sectoral productivity influences sectoral home bias, I build a symmetric two-country, two-sector model. The home country is better in producing one sector, while the foreign country is better in the other. Goods produced in different countries are not perfect substitutes, so sectoral prices react to productivity shocks to that sector in each country. Firms in each country and sector use country-specific capital and labor to produce goods. Shares of firms are traded internationally. Firms distribute capital income, in the form of dividends, to shareholders. Households construct optimal portfolios to maximize their expected lifetime utility.

## 4.1 Setup

Two countries ( $i = \{H, F\}$ ) both produce two types of consumption goods ( $s = \{a, b\}$ ). At time  $t$ , producers in country  $i$ , sector  $s$  (denoted as  $f_{i,s}$ ) employ sectoral productivity  $T_{i,s,t}$ , and combine labor  $L_{i,s,t}$  and capital  $K_{i,s,t}$  inputs in a Cobb-Douglas function<sup>9</sup>:

$$Y_{i,s,t} = T_{i,s,t} K_{i,s,t}^\alpha L_{i,s,t}^{1-\alpha}$$

Sectoral productivity  $T_{i,s,t}$  follows an AR(1) process over time with an autoregressive coefficient  $\rho_{i,s}$ , a long-term mean  $\bar{T}_{i,s}$  and i.i.d. shocks  $\epsilon_{i,s,t} \sim N(0, \sigma_\epsilon^2)$ :

$$T_{i,s,t} = \rho_{i,s} T_{i,s,t-1} + (1 - \rho_{i,s}) \bar{T}_{i,s} + \epsilon_{i,s,t}$$

Without loss of generality, I assume country  $H$  is more productive in sector  $a$  and country  $F$  is more productive in  $b$ . In the symmetric case, the long-term average productivity satisfies

$$\frac{\bar{T}_{H,a}}{\bar{T}_{H,b}} = \frac{\bar{T}_{F,b}}{\bar{T}_{F,a}} \equiv T > 1$$

where  $T$  denotes the difference between more productive and less productive sectors.

There is a stock market where firms sell their shares to both domestic and foreign households. Stocks are grouped into four types, each representing sector  $s$  in country  $i$ . Firms use  $1 - \alpha$  of their revenues to cover labor costs, and pay  $\alpha$  as dividends to their stock owners. In other words, dividends are claims to capital income:

$$d_{i,s,t} = p_{i,s,t} y_{i,s,t} - w_{i,s,t} l_{i,s,t} = \alpha p_{i,s,t} y_{i,s,t}$$

A representative household in country  $i$  has a constant-relative-risk-aversion (CRRA) preference. He chooses optimal consumption and asset holdings to maximize his expected lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{C_{i,t}^{1-\sigma}}{1-\sigma}$$

---

<sup>9</sup>Capital in this model is a fixed endowment, which does not require accumulation through investment. In another approach, [Heathcote and Perri \(2013\)](#) examine the influence of investment on portfolio choice.

Consumption is a constant-elasticity-of-substitution (CES) bundle of  $a$  and  $b$ .<sup>10</sup> The consumption weight is  $\psi_i$  for sector  $a$  and  $1 - \psi_i$  for sector  $b$  in country  $i$ .

$$C_{i,t} = (\psi_i^{\frac{1}{\phi}} C_{i,a,t}^{\frac{\phi-1}{\phi}} + (1 - \psi_i)^{\frac{1}{\phi}} C_{i,b,t}^{\frac{\phi-1}{\phi}})^{\frac{\phi}{\phi-1}}$$

Within each sector  $s$ , consumption is another CES bundle of goods produced at home and abroad:

$$C_{i,s,t} = (\mu_i^{\frac{1}{\eta}} C_{ii,s,t}^{\frac{\eta-1}{\eta}} + (1 - \mu_i)^{\frac{1}{\eta}} C_{ij,s,t}^{\frac{\eta-1}{\eta}})^{\frac{\eta}{\eta-1}}$$

where  $C_{ii,s,t}$  is the consumption of domestic goods and  $C_{ij,s,t}$  is for foreign goods. If domestic goods account for more than half of the consumption —  $\mu_i > \frac{1}{2}$  — countries exhibit consumption home bias.<sup>11</sup>

Preference is assumed to be symmetric in the baseline case.  $\psi_H = 1 - \psi_F \equiv \psi$  — the weight of  $a$  in  $H$  is equal to the weight of  $b$  in  $F$ .  $\mu_H = \mu_F$  — countries exhibit the same degree of consumption home bias. The goods market clearing condition in each sector is given by

$$C_{H,s,t} + C_{F,s,t} = Y_{H,s,t} + Y_{F,s,t}, \quad s \in \{a, b\}$$

In the stock market, a household purchases equities of country  $i$  sector  $s$  at time  $t$  for price  $q_{i,s,t}$ . Let  $\nu_{i,s,t}$  denote the number of shares a domestic household holds in country  $i$  sector  $s$  at time  $t$ , and  $\nu_{i,s,t}^*$  denote the asset holdings of a foreign household. Budget constraints of households at home and abroad, given by Equations 2 and 3 respectively, state that the sum of consumption expenditures and changes in asset positions is equal to the sum of labor income and dividend income.

$$P_{H,t} C_{H,t} + \sum_{s=\{a,b\}} [q_{H,s,t}(\nu_{H,s,t} - \nu_{H,s,t-1}) + q_{F,s,t}(\nu_{F,s,t} - \nu_{F,s,t-1})] = w_{H,t} L_{H,t} + \sum_{s=\{a,b\}} (d_{H,s,t} \nu_{H,s,t} + d_{F,s,t} \nu_{F,s,t}) \quad (2)$$

$$P_{F,t} C_{F,t} + \sum_{s=\{a,b\}} [q_{H,s,t}(\nu_{H,s,t}^* - \nu_{H,s,t-1}^*) + q_{F,s,t}(\nu_{F,s,t}^* - \nu_{F,s,t-1}^*)] = w_{F,t} L_{F,t} + \sum_{s=\{a,b\}} (d_{H,s,t} \nu_{H,i,t}^* + d_{F,s,t} \nu_{F,s,t}^*) \quad (3)$$

<sup>10</sup>In the home bias literature, the CES functional form is used in different contexts. For instance, Coeurdacier (2009) and Kollmann (2006) have a consumption composite of aggregate domestic and foreign goods. Alternatively, Tesar and Stockman (1995) and Matsumoto (2007) have a composite of tradables and nontradables. In my framework, consumption can be in any pair of sectors, whether tradable or not. If there is need to incorporate nontradables, I can introduce sectoral trade costs  $\tau \rightarrow \infty$ .

<sup>11</sup>Home bias in the goods market is a common assumption in the literature of asset home bias. For instance, Lewis (1999) examines consumption home bias and Heathcote and Perri (2013) study production home bias. Risk-hedging due to these biases has been proposed to explain why investors deviate from international diversification.

In the labor market, a household supplies one unit of labor inelastically. Labor is mobile within a country but immobile across borders. Hence, the wage rate is identical across sectors in country  $i$ :  $w_{i,a,t} = w_{i,b,t} = w_{i,t}$ . Without loss of generality, I normalize  $w_{F,t}$  to one and denote  $w_{H,t}$  as  $w_t$ . The labor market clearing condition follows

$$L_{i,a,t} + L_{i,b,t} = \bar{L}_i, \quad i \in \{H, F\}$$

Similarly, capital is mobile across sectors within country  $i$  at the rental rate of  $r_i$ . The capital market clearing condition states that

$$K_{i,a,t} + K_{i,b,t} = \bar{K}_i, \quad i \in \{H, F\}$$

With all the ingredients put together, the equilibrium of the model consists of a sequence of prices such as goods prices  $P_{i,s,t}, P_{i,t}, P_{s,t}$ , wages  $w_{H,t}, w_{F,t}, w_t$ , asset prices  $q_{i,s,t}$ , and dividends  $d_{i,s,t}$ , as well as a vector of quantities including output  $Y_{i,s,t}$ , consumption  $C_{i,s,t}, C_{i,t}$ , factors  $L_{i,s,t}, K_{i,s,t}$ , and asset holdings  $\nu_{i,s,t}$  such that:

- (a) Firms choose prices and quantities to maximize their profits;
- (b) Households choose consumption and equity holdings to maximize their expected lifetime utility;
- (c) Goods markets clear:  $C_{H,s,t} + C_{F,s,t} = Y_{H,s,t} + Y_{F,s,t}$ ,  $s \in \{a, b\}$ ;
- (d) Factor markets clear:  $K_{i,a,t} + K_{i,b,t} = \bar{K}_i$ ,  $L_{i,a,t} + L_{i,b,t} = \bar{L}_i$ ,  $i \in \{H, F\}$ ;
- (e) Equity markets clear:  $\nu_{i,s,t} + \nu_{i,s,t}^* = 1$  for  $i \in \{H, F\}, s \in \{a, b\}$ .

## 4.2 Sectoral Home Bias

I use [Devereux and Sutherland \(2007\)](#)'s perturbation method to solve the portfolio choice problem in this general equilibrium model. This method combines a second-order approximation of the portfolio Euler equation with a first-order approximation of other equations in the model to pin down the static optimal portfolio. Around the steady state of the model, this approach offers a unique solution where a country's holdings of productive and unproductive sectors' assets add up to zero:  $\nu_{Ha} + \nu_{Fb} = \nu_{Hb} + \nu_{Fa} = 0$ .

Since the analytical results are not illustrative enough, I analyze comparative statics graphically in order to examine the effect of sectoral productivity on sectoral home bias. As to parametrization, most values are standard in the macroeconomics and trade literature. For instance, the coefficient of relative risk aversion is 2 and the annual dis-

count factor is 0.95. In terms of preference, the consumption weight of each sector is 0.5, while the weight of domestic goods in each sector is assumed to be 0.6 to capture the consumption home bias observed in the real world. Moreover, I follow [Levchenko and Zhang \(2016\)](#) in setting the elasticity of substitution between broad sectors  $\phi$  equal to 2. Within a sector, the elasticity of substitution between domestic and foreign goods is assumed to be 2, consistent with the large values estimated with bilateral sectoral trade data (see [Hummels \(1999\)](#)). Last, the autoregressive coefficient and standard deviation of technology take the value of 0.9 and 0.025 respectively. Parameter values in the benchmark case are listed in [Table 1](#). [Appendix B.1](#) assumes alternative parameter values and shows that results are qualitatively the same.

[Figure 6](#) plots the numerical solution to asset holdings in the benchmark model. The

Table 1: Parametrization in the Benchmark Case

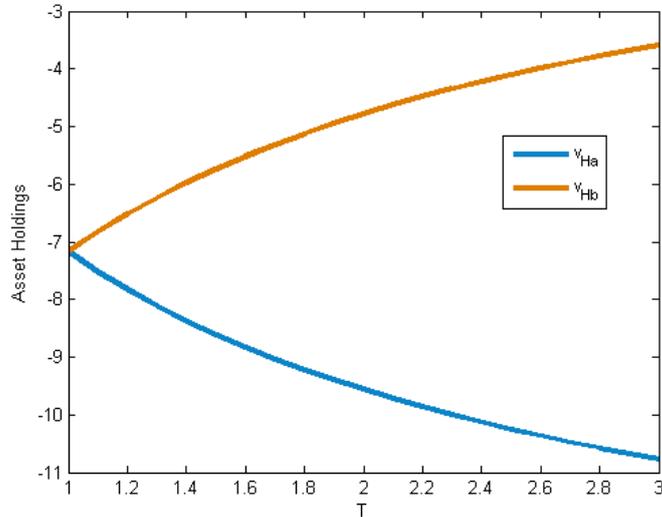
Parameter	Description	Value
$\beta$	Discount factor	0.95
$\sigma$	Coefficient of relative risk aversion	2
$\psi$	Weight of a sector in consumption	0.5
$\mu$	Weight of domestic goods in a sector	0.6
$\phi$	Elasticity of substitution between sectors	2
$\eta$	Elasticity of substitution within sectors	2
$\rho$	Autoregressive coefficient of technology	0.9
$\sigma_\epsilon$	Std. dev. of technology shocks	0.025

two lines depict domestic households' holdings of domestic assets: the blue line is the position of the more productive sector ( $\nu_{H,a}$ ), and the orange line is for the less productive sector ( $\nu_{H,b}$ ). The unit on the y-axis is asset holdings as shares of income in the steady state  $\bar{Y}_H$ .  $T = \frac{\bar{T}_{H,a}}{\bar{T}_{H,b}}$  measures the productivity disparity between the two sectors.

When the value of  $T$  rises from 1 to 3,  $\nu_{H,a}$  decreases and  $\nu_{H,b}$  increases, while  $\nu_{H,a}$  is consistently below  $\nu_{H,b}$ . The interpretation is that, the two sectors display the same degree of home bias when  $T = 1$  since there is no sectoral productivity difference and hence the two sectors are identical under this assumption. When  $T$  rises, countries become more specialized in production and trade as the relative productivity gap widens. Therefore, the productive sector  $f_{H,a}$  is exposed to greater risk since its correlation with labor income rises. As a result, domestic households decrease holdings of  $f_{H,a}$  and increase holdings of  $f_{H,b}$  assets.

In order to further explain the mechanism, [Table 2](#) lists the correlation between asset returns ( $r_{i,s}, i \in \{H, F\}, s \in \{a, b\}$ ) and labor income ( $wL$ ) when  $T = 3$ . From the

Figure 6: Sectoral Home Bias and Productivity Difference  $T$



table,  $r_{H,a}$  has the greatest correlation, followed by  $r_{H,b}$  and then  $r_{F,b}$ , while  $r_{F,a}$  has the least correlation with  $wL$ . Since  $f_{F,a}$  provides the best hedge and  $f_{H,a}$  provides the worst hedge against labor income risk among the four assets, investors show greater home bias in sector  $b$  than in sector  $a$ .

These theoretical results, consistent with the empirical findings in Section 3.4 of the paper, illustrate why sectoral productivity influences sectoral home bias.

Table 2: Asset Returns' Correlation with Labor Income

	$r_{H,a}$	$r_{H,b}$	$r_{F,a}$	$r_{F,b}$
$\rho(wL, r_{i,s})$	0.270	0.266	-0.041	0.210

Note: This table lists the correlation between the sectoral financial returns of country  $i$  sector  $s$  and the home labor income  $wL$ .

### 4.3 Model Extension

In this section, I extend the benchmark model by incorporating nontradable sectors. I now assume sector  $a$  is tradable and sector  $b$  is not. Table 3 compares the results in the baseline case and in the extended case with nontradables.

The table shows that while domestic holdings are negative in the baseline model,

Table 3: Asset Holdings with and without Nontradables

	Baseline Model	Model with Nontradables
$\nu_{Ha}$	-10.76	2.01
$\nu_{Hb}$	-3.59	3.37
$\nu_{Fa}$	3.59	4.41
$\nu_{Fb}$	10.76	-9.79
$HB_a$	-0.12	0.33
$HB_b$	-0.04	58.35

Note: This table lists the numerical results of asset holdings and home bias in the baseline case with only tradable sectors and the extended case with nontradables.

they turn positive in the extended model. This result can also be understood from the risk-hedging perspective. Introducing nontradable sectors into the model limits international goods flows, which consequently strengthens the correlation between domestic asset returns and consumption. Hence, households do not circumvent domestic assets as before since these assets insure households against fluctuations in domestic consumption. Furthermore, home bias is much stronger in the nontradable sector than in the tradable sector, since the former provides a better hedge against consumption volatility. Meanwhile, investors short assets in the foreign nontradable sector. Since shocks to that sector do not directly affect home consumption, holding the sector's assets offers little risk-hedging benefit. This theoretical result not only resonates with arguments by Obstfeld and Rogoff (2001) and Collard et al. (2007), but also accounts for the empirical findings in Section 3.2 of this paper.

## 5 Conclusion

This paper examines the well-known home bias phenomenon in international finance by adding the sectoral dimension to the literature. First, I compile the industry-level home bias of 27 sectors in 43 countries using unique financial datasets. This novel index provides unprecedentedly rich and detailed data for studying home bias. Second, I empirically explore the determinants of sectoral home bias, including country-, sector-, and time-specific factors.

My empirical findings are (1) home bias is stronger when and where capital flow restrictions are greater, (2) nontradable sectors exhibit stronger home bias than tradable sectors, and (3) sectoral home bias decreases in sectoral productivity. These findings

verify various explanations for home bias including international market frictions and risk-hedging by investors.

In particular, the negative correlation of sectoral productivity with home bias prompts me to build a theoretical model with a multi-sectoral setting. This setup, different from the framework in most studies of home bias that abstracts from sectoral heterogeneity, extends and deepens our understanding of investors' risk-hedging patterns as reflected in their portfolio choices.

Furthermore, this analysis of sectoral home bias motivates me to study national home bias from the angle of industrial structure (Hu (2017)). In a multi-sectoral setting, investors are able to risk-hedge not only by holding assets in different countries (inter-country risk-hedging) but also by holding domestic assets in different sectors (intra-country risk-hedging). If the covariance across domestic assets ensures efficient risk-hedging, there is less need for investors to hold foreign equities. Therefore, industrial specialization has important implications for national home bias.

The framework in this paper can be extended in several directions for future research. First, we can introduce corporate debt into the model to investigate the complementarity as well as substitutability between debt and equity. Coeurdacier and Gourinchas (2016) discuss the differences between debt and equity in risk-hedging at the national level, but there is little research at the industry level with corporate instead of government debt. Second, this paper focuses on the effect of industrial structure on portfolio choices, while future studies can examine the impact of asset allocations on real production when firms face financial constraints. By including these extensions, future research will provide us with a better understanding of the interplay between industrial structure and home bias.

## References

- Baxter, M. and Jermann, U. J. The international diversification puzzle is worse than you think. *American Economic Review*, 87(1):170–180, 1997.
- Braun, M. Financial contractability and asset hardness. 2005.
- Chinn, M. D. and Ito, H. What matters for financial development? capital controls, institutions, and interactions. *Journal of Development Economics*, 81(1):163–192, 2006.
- Coeurdacier, N. Do trade costs in goods market lead to home bias in equities? *Journal of International Economics*, 77(1):86–100, 2009.
- Coeurdacier, N. and Gourinchas, P.-O. When bonds matter: Home bias in goods and assets. *Journal of Monetary Economics*, 82:119–137, 2016.
- Coeurdacier, N. and Rey, H. Home bias in open economy financial macroeconomics. *Journal of Economic Literature*, 51(1):63–115, 2013.
- Cole, H. L. and Obstfeld, M. Commodity trade and international risk sharing: How much do financial markets matter? *Journal of Monetary Economics*, 28(1):3–24, 1991.
- Collard, F., Dellas, H., Diba, B., and Stockman, A. Goods trade and international equity portfolios. Technical report, National Bureau of Economic Research, 2007.
- Devereux, M. B. and Sutherland, A. Country portfolio dynamics. *IMF Working Papers*, pages 1–27, 2007.
- French, K. R. and Poterba, J. M. Investor diversification and international equity markets. *American Economic Review*, pages 222–226, 1991.
- Harberger, A. C. Perspectives on capital and technology in less-developed countries. *Estudios de Economía (Chile)*, 1988.
- Heathcote, J. and Perri, F. The international diversification puzzle is not as bad as you think. *Journal of Political Economy*, 121(6):1108–1159, 2013.
- Hu, C. Industrial specialization matters: a new angle on equity home bias. Technical report, 2017.
- Hummels, D. L. Toward a geography of trade costs. 1999.

- Inklaar, R. and Timmer, M. Capital, labor and tfp in pwt8.0. *Groningen Growth and Development Centre, University of Groningen*, 2013.
- Isaksson, A. World productivity database: A technical description. *Research and Statistics Staff Working Paper*, 10:2007, 2007.
- Karabarbounis, L. and Neiman, B. The global decline of the labor share. *Quarterly Journal of Economics*, 129(1):61–103, 2013.
- Kollmann, R. International portfolio equilibrium and the current account. 2006.
- Lane, P. R. and Milesi-Ferretti, G. M. International financial integration. *IMF Economic Review*, 50(1):82–113, 2003.
- Levchenko, A. A. and Zhang, J. The evolution of comparative advantage: Measurement and welfare implications. *Journal of Monetary Economics*, 78:96–111, 2016.
- Lewis, K. K. Trying to explain home bias in equities and consumption. *Journal of Economic Literature*, 37(2):571–608, 1999.
- Lewis, K. K. Global asset pricing. *Annual Review of Financial Economics*, 3(1):435–466, 2011.
- Mano, R. and Castillo, M. The level of productivity in traded and non-traded sectors for a large panel of countries. (15-48), 2015.
- Matsumoto, A. The role of nonseparable utility and nontradeables in international business cycles and portfolio choice. *IMF Working Papers*, pages 1–32, 2007.
- Obstfeld, M. and Rogoff, K. The six major puzzles in international macroeconomics: is there a common cause? In *NBER Macroeconomics Annual 2000, Volume 15*, pages 339–412. MIT Press, 2001.
- Pesenti, P. and Van Wincoop, E. Can nontradables generate substantial home bias? *Journal of Money, Credit and Banking*, pages 25–50, 2002.
- Stockman, A. C. and Dellas, H. International portfolio nondiversification and exchange rate variability. *Journal of International Economics*, 26(3-4):271–289, 1989.
- Stulz, R. A model of international asset pricing. *Journal of Financial Economics*, 9(4):383–406, 1981.

- Stulz, R. M. International portfolio choice and asset pricing: An integrative survey. *Handbooks in Operations Research and Management Science*, 9:201–223, 1995.
- Tesar, L. L. International risk-sharing and non-traded goods. *Journal of International Economics*, 35(1):69–89, 1993.
- Tesar, L. L. and Stockman, A. C. Tastes and technology in a two-country model of the business cycle: Explaining international comovements. *American Economic Review*, 85(1):168–185, 1995.
- Tesar, L. L. and Werner, I. M. Home bias and high turnover. *Journal of International Money and Finance*, 14(4):467–492, 1995.

# Appendices

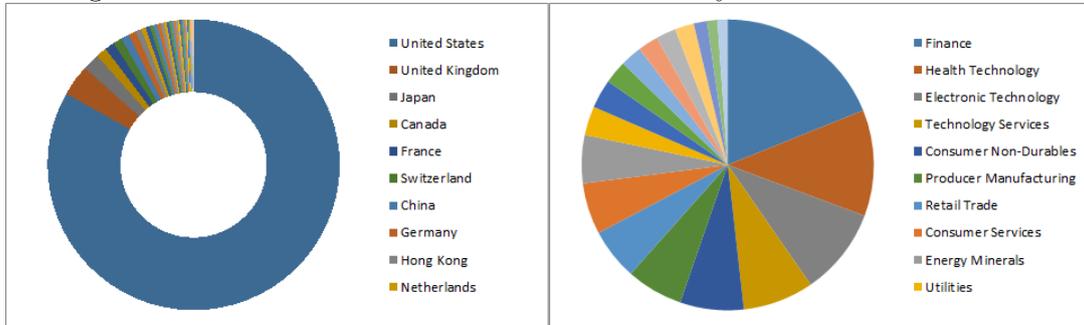
## A Tables and Figures

Table A.1: Top Twenty U.S. Institutional Investors by Assets

Name	Equity Assets (\$)	Location
The Vanguard Group, Inc.	1,607,502,939,834	PA
BlackRock Fund Advisors	1,216,454,636,413	CA
SSgA Funds Management, Inc.	1,000,113,734,436	MA
Fidelity Management & Research Co.	818,423,292,122	MA
T. Rowe Price Associates, Inc.	505,493,540,323	MD
Capital Research & Management Co.	458,524,984,616	CA
Wellington Management Co. LLP	410,550,019,151	MA
Capital Research & Management Co.	405,170,640,206	CA
Northern Trust Investments, Inc.	343,990,576,944	IL
Massachusetts Financial Services Co.	267,025,899,324	MA
JPMorgan Investment Management, Inc.	247,083,106,467	NY
Dimensional Fund Advisors LP	234,054,032,158	TX
BlackRock Advisors LLC	193,125,056,156	NY
Mellon Capital Management Corp.	191,980,125,222	CA
TIAA-CREF Investment Management LLC	187,726,247,974	NY
Geode Capital Management LLC	173,264,747,809	MA
Invesco Advisers, Inc.	170,566,991,974	GA
Columbia Management Investment Advisers LLC	155,105,284,565	MA
Dodge & Cox	153,491,210,142	CA
OppenheimerFunds, Inc.	147,243,417,222	NY

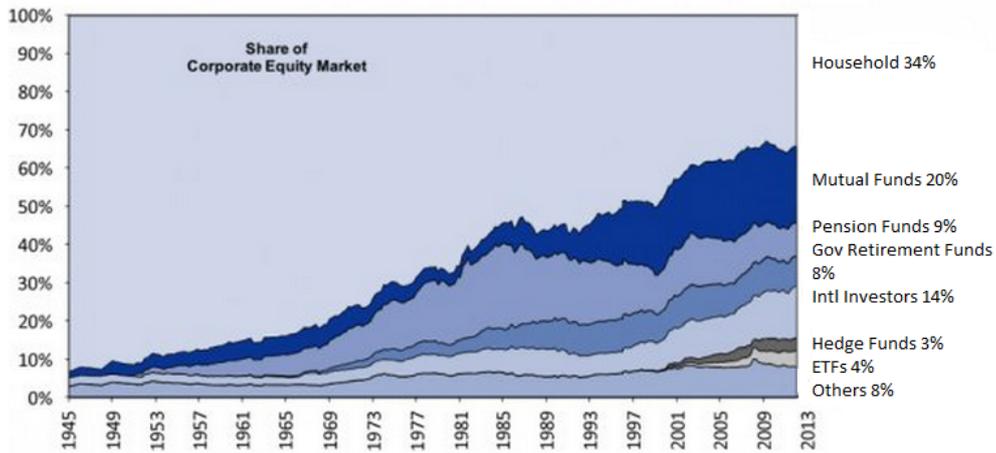
Note: This table lists the name, asset size and location of the 20 largest U.S. institutional investors as of 2014Q3. The data source is Factset/Lionshare.

Figure A.1: U.S. Institutional Investors' Country and Sector Allocation



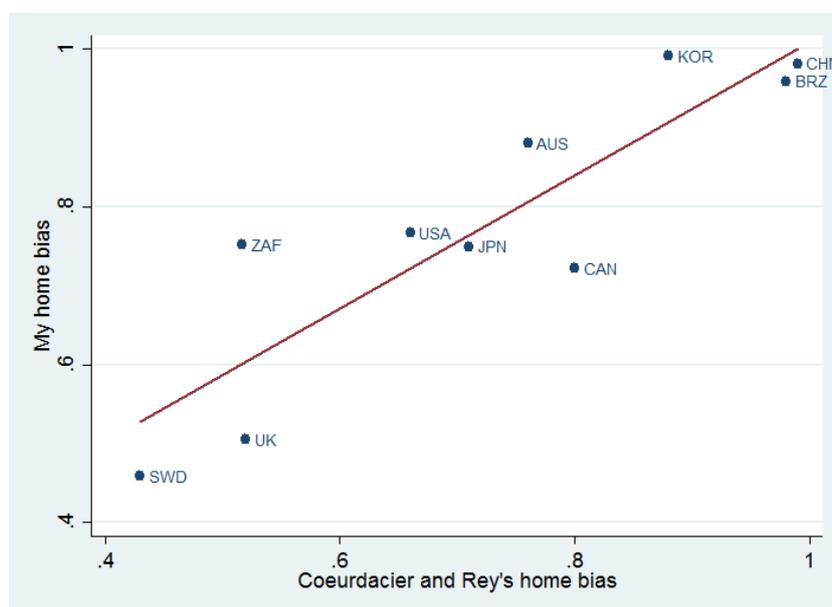
Note: This figure shows U.S. institutional investors' equity portfolio on Jan. 5, 2015. The source is the ownership data from Factset/Lionshare. The left chart is the allocation across countries, and the right chart is the allocation across sectors.

Figure A.2: Ownership in the U.S. Corporate Equity Market



Note: This figure shows the historical trend for ownership in the US equity market since WWII. The data source is Federal Reserve Board St. Louis. The figure shows that institutional investors have replaced households as the largest owners of U.S. equities.

Figure A.3: Comparison of Home Bias Constructed with Factset/Lionshare Data and IFS Data



Note: This figure plots my national home bias index against [Coourdacier and Rey \(2013\)](#)'s (both as of 2008). I use the Factset/Lionshare data to construct the index while they use the IFS data. The two indices are consistent since most of the points lie on or close to the 45-degree line.

Table A.2: Correspondence between Factset and Datastream Industries

Factset Code	Description	ICB	Description
2405 2410	Foods: Major Diversified;	FOODS	Food Producers
2415	Foods: Specialty/Candy; Foods: Meat/Fish/Dairy		
2420 2425	Beverages: Non-Alcoholic; Beverages: Alcoholic	BEVES	Beverages
2430	Tobacco	TOBAC	Tobacco
2440	Apparel; Footware	CLTHG	Clothing & Accessories, Footwear
1130	Forest Products	FORST	Forestry
2230	Pulp & Paper	FSTPA	Paper
2100	Energy Minerals(gas and oil production, coal)	OILGP, COALM	Oil & Gas Producers
2205 2210	Chemicals: Major Diversified ;	CHMCL	Chemicals
2215	Chemicals: Specialty; Chemicals: Agricultural		
2305 2310	Pharmaceuticals: Major;	PHARM	Pharmaceuticals & Biotechnolog
2315	Pharmaceuticals: Other; Pharmaceuticals: Generic		
1105	Steel	STEEL	Iron & Steel
1115 1120	Aluminum; Precious Metals;	NOFMS	Nonferrous Metals
1125	Other Metals/Minerals		
1300	Electronic Technology	ELTNC	Electronics & Electric Equipment
1210	Industrial Machinery	IMACH	Industrial Machinery
1405	Motor Vehicles	AUTMB	Automobiles & Parts
1420	Home Furnishings	FURNS	Furnishings
4700	Utilities(Electric Utilities, Gas Distributors, Water Utilities, Alternative Power Generation)	UTILS	Utilities
3115	Engineering & Construction	HVYCN	Heavy Construction
3500	Retail Trade	RTAIL	Retail
4615 4620	Trucking ; Railroads	TRUCK RAILS	Trucking ; Railroads
4625	Marine Shipping	MARIN	Marine Transportation
4610	Airlines	AIRLN	Airlines
3435 3440	Restaurants; Hotels/Resorts/Cruiselines	RESTS,HOTEL	Restaurants & Bars; Hotels
3420 3425	Publishing: Newspapers; Publishing: Books/Magazines	PUBLS	Publishing
3405 3410	Broadcasting; Cable/Satellite TV;	BRDEN	Broadcasting & Entertainment
3415	Media Conglomerates		
4900	Telecommunications	TELCM	Telecommunications
4800	Finance	FINAN	Financials
4885	Real Estate Development	RLEST	Real Estate

Note: ICB stands for Dow Jones/FTSE's Industry Classification Benchmark. FactSet reports its own industry and sector classifications.

Table A.3: Correspondence between My Industry Code and ISIC 4

Industry Name	My Code	ISIC 4
Food Producers	1	151, 153, 1520, 154
Beverages	2	155
Tobacco	3	1600
Clothing & Accessories, Footwear	4	1810, 1820
Forestry	5	202
Paper	6	210
Oil & Gas Producers,Coal	7	2310, 2320
Chemicals	8	241, 242
Pharmaceuticals	9	2423
Iron & Steel	10	2710
Nonferrous Metals	11	2720
Electronics & Electrical Equipment	12	3110, 3190, 3210
Industrial Machinery	13	291, 292
Automobiles & Parts	14	3410, 3420, 3430
Furnishings	15	3610
Trucking ; Railroads	20	3520
Marine Transportation	21	351
Publishing	24	221

Note: ISIC Rev.4. stands for International Standard Industrial Classification of All Economic Activities, Rev.4.

Table A.4: Sectoral Home Bias Index

sector	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	
AU	0.46	0.69		0.86	0.32	0.63	0.93	0.59	0.67	0.93	0.92	0.25	0.28	0.31		0.63	0.83	0.87	0.79	0.91	0.69	0.95	0.26	0.93	0.65	0.65	0.88	
OE	0.00	0.00		0.13			0.00	0.16	0.01	0.56		0.02	0.39	0.08		0.11	0.13		0.32			-	0.01			0.10	0.10	
BA																	0.28	0.02	0.08							0.91	0.90	
BG	0.02	0.34		0.10				0.30	0.10		0.24	0.10	0.00			0.00	0.21	0.24	0.16		0.44		0.00	0.07	0.00	0.13	0.24	
BR	0.70	0.73	0.98	0.98		1.00	0.55	0.81		0.86		0.79	0.85	0.88		0.77	0.72	0.46	0.61	0.99		0.33			0.15	0.43	0.77	
CN	0.23	0.09	-	0.41	0.92	0.05	0.82	0.64	0.10	0.04	0.72	0.24		0.57	0.42	0.37	0.61	0.37	0.27	0.87		0.27	0.20	0.23	0.39	0.54	0.71	
CL	0.54	0.75	0.01	0.96	1.00	-	0.00	0.49	0.95	0.55	0.80					0.74	0.88	0.71	0.90		1.00	0.98				0.77	0.78	
CA	0.94	0.93	0.00	0.96	1.00	1.00	0.83	0.95	0.96	1.00	0.68	0.99	0.98	0.99	1.00	0.80	0.99	0.89	0.57	1.00	0.63	0.95	0.80	0.63	0.92	0.54	0.92	
CZ	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00							-	0.00	0.00	0.00		0.00		0.00		0.00	0.00	0.00	
DK	-	0.31		0.27				0.10	0.30			0.09	-			0.01	0.42	0.00	0.16	0.34	0.51				0.13	0.13	0.14	
FN	0.01												0.04				0.75	0.90	0.61	0.60		0.78	0.83		0.68		0.26	0.45
FR	0.38	0.25				0.99	0.00	0.63	0.08	0.77	0.69	0.82	0.77	0.00		0.75	0.90	0.61	0.60		0.78	0.83		0.68		0.26	0.45	
BD	0.62	0.32		0.63		0.16	0.02	0.31	0.32	-	0.07	0.16	-	0.35		0.36	0.74	0.41	0.70	0.20	-	0.32	0.35	0.28	0.23	0.40	0.37	
GR	0.03	0.00		0.17	0.05	-	0.00	0.51	0.18	0.11	0.01	-	0.07	0.23	0.67	-	0.24	0.26	0.07	0.29	0.00	0.03		0.07	0.04	0.13	0.21	
IR	0.15	-	0.00	0.00		0.03	0.00	0.00	0.00	0.03	0.05	0.02	0.32		0.01	0.14	0.36	0.29	0.59			0.08	0.06	0.08	0.00	0.13	0.15	
HK	0.34	0.01		0.18	-	0.11	0.34	0.13	0.08	-	0.00	0.10	0.06	0.01	0.25	0.38	0.05	0.48	0.63		0.17	0.11	0.35	0.18	0.11	0.31	0.06	
HN	0.00	0.61		0.06			0.00	0.58	0.22				0.00	0.00		0.26		0.00	0.16				0.59		0.00	0.36	0.33	
IS	0.38	0.05					0.07	0.00	0.00						0.03		0.00	0.00	0.00			0.48	0.00	0.22	0.00	0.00	0.37	
IT	0.60			0.91			0.81	0.94	0.46			0.82	0.84			0.86	0.98	0.64	0.90			0.72	0.50		0.44	0.57	0.85	
JP	0.08	0.07		0.40		0.07	-	0.02	0.01	-	0.00	0.02	0.30	0.16	0.47	0.50	0.28	0.01	0.07	0.00	0.20	0.00	0.37	0.45	0.36	0.08	0.39	
KO	0.54	0.32	0.14	0.46		0.58	0.10	0.61	0.34	0.65	0.20	0.43	0.79	0.81	0.18	0.36	0.88	0.45	0.77	0.68	0.94	0.40	0.23	-	0.33	0.25	0.37	
KW	0.97	0.80	0.63	0.90		0.94	0.86	0.98	0.85	0.99	0.73	0.88	0.99	0.98	0.97	0.98	1.00	0.91	0.06		1.00	0.97	0.86		0.81	0.93	0.90	
LX	0.25	0.00					0.10	0.11				0.00				0.07	0.00	0.49			0.00	0.00				0.77	0.28	
	0.00	0.00								-		0.00				0.00		0.00	0.00		0.00				-	0.00	0.00	
										0.02																0.03		

Note: The formula used to create the index is  $HB_{i,s} = 1 - \text{Share of Sector } s \text{ Foreign Equities in Country } i \text{ Equity Holdings} / \text{Share of sector } s \text{ Foreign Equities in the World Market Portfolio}$ . The data are from Factset/Lionshare and Datastream. The index covers 27 sectors in 43 countries. There are 834 observations in total, with mean 0.42 and std. dev. 0.36. The histogram is shown in Figure 1.

Table A.5: Sectoral Home Bias Index (Continued)

sector	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
MY		0.99	0.94	0.27	1.00	0.98	0.01	0.98		0.98		0.93	0.76	1.00		1.00	0.98	0.54	0.98		1.00	1.00	0.97	0.93	0.98	0.98	0.98
MX		0.98						0.94	0.86	0.45	0.95			-		0.13	1.00	1.00	0.96			0.14	1.00		1.00	0.99	0.78
NL	0.18	0.14		0.00		0.03		0.11	0.00	-		0.05	0.06	0.03	0.00		0.20	0.16	0.01		-		0.00	0.61	0.00	0.08	0.11
NZ	0.52	0.19		0.00	0.87	-	0.19	0.63	0.03	0.31		0.10	0.17	0.00		0.80		0.60	0.66	0.00		0.82	0.51	0.00	0.73	0.82	0.39
NW	0.05				0.01	0.31	0.01	0.13	0.00			0.01	-		0.53	0.07	0.13	0.00	0.12		0.45	0.09		0.35		0.11	0.04
PH	0.17	-					0.72		0.00		0.45	0.06				0.40		0.15	0.70			0.19	0.00		0.02	0.60	0.36
PO	0.95	0.86		0.92		1.00	0.92	0.92	0.62	0.88	0.99	0.55	0.95	0.91		0.73	0.98	0.90	0.82	0.92			0.98	0.95	0.68	0.96	0.91
PT	0.00	0.10				0.98	0.00	0.00	0.00	0.00		0.03		0.10		0.76	0.56	0.50	0.00		0.00		0.16	0.76	0.87	0.63	0.59
QA																0.00		0.00	1.00		1.00					0.94	0.55
RM	1.00	0.87		0.00		1.00	1.00	0.93	1.00	0.91		0.29	0.90	1.00		1.00	0.94	0.55	0.97				1.00				1.00
RS	1.00						0.61	1.00	1.00	0.37	0.09		1.00	1.00		1.00	1.00	1.00	0.10		1.00	1.00				0.90	0.95
SG	0.06	-		0.00			0.00	0.00	0.00	0.00	0.00	0.09	0.04		0.12	0.00	0.08	0.02	0.41		0.13	0.50	0.14	0.38	0.00	0.09	0.11
SL	0.51	0.74		0.00			0.00	0.75	0.93			0.00	0.00	0.18	0.00		0.12	0.79		0.66			0.57	0.00		0.52	0.38
SA	0.97	0.01				0.89	1.00	0.96	0.81	0.98		0.53			1.00	0.00	0.99	0.87	0.51		1.00			0.20	0.84	0.77	0.70
ES	0.35	0.32	-	0.16	0.67	0.26	0.03	0.05	0.14	0.64	0.00	0.02	0.11	0.05		0.76	0.82	0.01	0.75				0.55	0.08	0.50	0.51	0.46
SD	0.08		0.02			0.47	0.19	0.00	0.08	0.58	0.19	0.54	0.91	0.04	0.61	0.00	0.77	0.69	0.61			0.29	0.12	0.00	0.53	0.45	0.54
SW	0.27		0.43		0.57	0.11	0.00	0.25	0.18	0.02		0.03	0.21	0.05		-	0.02	0.07	0.26		0.31	-	0.00	0.03		0.04	0.24
TA	0.55			0.49			0.00	0.66		0.72		0.86	0.57	0.45				0.28	0.22		0.68	0.60				0.74	0.61
AE	0.00	0.05							0.00							0.00	0.43		0.42			0.85	0.45			0.54	0.61
UK	0.27	0.35	0.55	0.27		0.21	0.14	0.20	0.46	0.01		0.08	0.32	0.12	0.20	0.45	0.42	0.42	0.28	0.03	0.13	0.17	0.61	0.63	0.27	0.51	0.43
US	0.77	0.69	0.77	0.82	0.75	0.75	0.83	0.74	0.64	0.47	0.31	0.81	0.44	0.48	0.92	0.82	0.65	0.81	-	0.63	0.48	0.63	0.78	0.42	0.80	0.53	0.77
																				0.02							

Note: This table lists the sectoral home bias index. The formula of the index is  $HB_{i,s} = 1 - \text{Share of Sector } s \text{ Foreign Equities in Country } i \text{ Equity Holdings} / \text{Share of sector } s \text{ Foreign Equities the World Market Portfolio}$ . The data are from Factset/Lionshare and Datastream. The index covers 27 sectors in 43 countries. There are 834 observations in total, with mean 0.42 and std. dev. 0.36. The histogram is shown in Figure 1.

Table A.6: Country and Sector Codes

Country/Region	Code	Country/Region	Code	Sector	Code
Australia	AU	Norway	NW	Food Producers	1
Austria	OE	Philippines	PH	Beverages	2
Bahrain	BA	Poland	PO	Tobacco	3
Belgium	BG	Portugal	PT	Clothing & Accessories, Footwear	4
Brazil	BR	Qatar	QA	Forestry	5
Canada	CN	Romania	RM	Paper	6
Chile	CL	Russia	RS	Oil & Gas Producers, Coal	7
China	CA	Singapore	SG	Chemicals	8
Czech Republic	CZ	South Africa	SA	Pharmaceuticals	9
Denmark	DK	Slovenia	SL	Iron & Steel	10
Finland	FN	Spain	ES	Nonferrous Metals	11
France	FR	Sweden	SD	Electronics & Electric Equipement	12
Germany	BD	Switzerland	SW	Industrial Machinery	13
Greece	GR	Taiwan	TA	Automobiles & Parts	14
Hong Kong	HK	U.A.E.	AE	Furnishings	15
Hungary	HN	United Kingdom	UK	Utilities	16
Ireland	IR	United States	US	Heavy Construction	17
Israel	IS			Retail	18
Italy	IT			Real Estate	19
Japan	JP			Trucking ; Railroads	20
Korea	KO			Marine Transportation	21
Kuwait	KW			Airlines	22
Luxembourg	LX			Restaurants & Bars; Hotels	23
Malaysia	MY			Publishing	24
Mexico	MX			Broadcasting & Entertainment	25
Netherlands	NL			Telecommunications	26
New Zealand	NZ			Finance	27

Note: This table defines the abbreviation of countries and sectors listed in Table [A.4](#).

Table A.7: Sectoral Home Bias and Country Effects

Dep. Var: Sectoral $HB$	( 1 )	( 2 )	( 3 )	( 4 )
OECD	-0.186 *** ( 0.029 ) [ -0.515 ]	-0.184 *** ( 0.029 ) [ -0.510 ]		
Chinn-Ito			-0.174 *** ( 0.009 ) [ -0.549 ]	-0.174 *** ( 0.009 ) [ -0.550 ]
Constant	0.555 *** 0.026	0.506 *** ( 0.056 )	0.713 *** ( 0.019 )	0.675 *** ( 0.044 )
Sector FE	N	Y	N	Y
Observations	834	834	792	792
$R^2$	0.053	0.086	0.301	0.338

Note: Robust standard errors in parentheses and standardized coefficients in brackets.\*\*\*significant at 1%. The dependent variable is sectoral home bias. The independent variables are the OECD dummy, the Chinn-Ito index, and sector fixed effects.

Table A.8: Sectoral Home Bias and Sector Effects

Dep. Var: Sectoral $HB$	( 1 )	( 2 )	( 3 )	( 4 )
Tradable	-0.055 *** ( 0.025 ) [ -0.151 ]	-0.071 *** ( 0.016 ) [ -0.197 ]		
Labor intensity			-0.026 ( 0.082 ) [ -0.07 ]	-0.096 * ( 0.057 ) [ -0.065 ]
Constant	0.448 *** ( 0.017 )	0.713 *** ( 0.047 )	0.436 *** ( 0.090 )	0.764 *** ( 0.103 )
Country FE	N	Y	N	Y
Observations	834	834	328	328
$R^2$	0.006	0.592	0.0003	0.635

Note: Robust standard errors in parentheses and standardized coefficients in brackets.\*\*\*significant at 1%, \*\* at 5%, and \* at 10%. The dependent variable is sectoral home bias. The independent variables are a dummy for tradable sectors, sectoral labor intensity, and country fixed effects.

Table A.9: Sectoral Home Bias and Time Effects

Dep. Var: Dynamic Sectoral $HB_t$	( 1 )	( 2 )	( 3 )
Year	-0.006 *** ( 0.001 ) [ -0.014 ]	-0.003 * ( 0.002 ) [ -0.008 ]	0.007 ** ( 0.003 ) [ 0.018 ]
Tradable		10.146 ** ( 4.226 ) [ 26.23 ]	
Year $\times$ Tradable		-0.005 ** ( 0.002 ) [ -0.013 ]	
OECD			30.189 *** ( 6.625 ) [ 78.045 ]
Year $\times$ OECD			-0.015 *** ( 0.003 ) [ -0.039 ]
Constant	11.781 *** ( 2.064 )	6.562 *** ( 3.032 )	-13.460 *** ( 5.718 )
Country FE	Y	Y	N
Sector FE	Y	N	Y
Observations	8,137	8,137	8,137
$R^2$	0.536	0.512	0.085

Note: Robust standard errors in parentheses and standardized coefficients in brackets. \*\*\*significant at 1%, \*\* at 5%, and \* at 10%. The dependent variable is dynamic sectoral home bias. The independent variables are year, dummies for tradable sectors and OECD countries, and country or sector fixed effects.

Table A.10: Sectoral Home Bias and Productivity Effects

Dep. Var: Sectoral HB	( 1 )	( 2 )	( 3 )	( 4 )
Log(TFP1)	-0.058 *** ( 0.004 ) [ -0.142 ]	-0.091 *** ( 0.005 ) [ -0.238 ]	-0.098 *** ( 0.005 ) [ -0.252 ]	-0.031 *** ( 0.006 ) [ -0.093 ]
Constant	0.571 *** ( 0.022 )	0.693 *** ( 0.032 )	0.515 *** ( 0.044 )	0.729 *** ( 0.075 )
Sector FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Country FE	No	No	No	Yes
Observations	2,932	2,932	2,932	2,932
$R^2$	0.073	0.156	0.206	0.520
Dep. Var: Sectoral HB	( 1 )	( 2 )	( 3 )	( 4 )
Log(TFP2)	-0.054 *** ( 0.004 ) [ -0.160 ]	-0.093 *** ( 0.005 ) [ -0.258 ]	-0.098 *** ( 0.005 ) [ -0.261 ]	-0.032 *** ( 0.006 ) [ -0.074 ]
Constant	0.567 *** ( 0.022 )	0.716 *** ( 0.033 )	0.535 *** ( 0.044 )	0.746 *** ( 0.075 )
Sector FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Country FE	No	No	No	Yes
Observations	2,927	2,927	2,927	2,927
$R^2$	0.064	0.156	0.202	0.521
Dep. Var: Sectoral HB	( 1 )	( 2 )	( 3 )	( 4 )
Log(TFP3)	-0.063 *** ( 0.004 ) [ -0.151 ]	-0.101 *** ( 0.005 ) [ -0.234 ]	-0.102 *** ( 0.005 ) [ -0.252 ]	-0.029 *** ( 0.007 ) [ -0.091 ]
Constant	0.620 *** ( 0.025 )	0.779 *** ( 0.035 )	0.610 *** ( 0.047 )	0.748 *** ( 0.076 )
Sector FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Country FE	No	No	No	Yes
Observations	2,895	2,895	2,895	2,895
$R^2$	0.075	0.165	0.202	0.518

Note: Robust standard errors in parentheses and standardized coefficients in brackets.\*\*\*significant at 1%, \*\* at 5%, and \* at 10%. The dependent variable is dynamic sectoral home bias. The independent variables are dynamic sectoral TFP with capital stock measured in different ways.  $TFP_1$  uses [Inklaar and Timmer \(2013\)](#)'s method,  $TFP_2$  uses [Isaksson \(2007\)](#)'s, and  $TFP_3$  uses [Harberger \(1988\)](#)'s. Country, sector, and time fixed effects are also considered in the regressions.

Table A.11:  $\text{Corr}(w_i L_i, r_{i,s})$  and Sectoral productivity  $\bar{TFP}_{i,s}$ 

Dependent Variable: $\text{Corr}(w_i L_i, r_{i,s})$	( 1 )	( 2 )
Sectoral TFP	0.039 *	0.031 *
	( 1.65 )	( 1.68 )
Country FE	Y	Y
Sector FE	N	Y
Observations	329	329
$R^2$	0.134	0.325

Note: Coefficients are standardized and t-statistics are in parentheses. \*significant at 10%. The dependent variable is the correlation between sectoral home bias and national labor income. The independent variable is sectoral TFP calculated with [Inklaar and Timmer \(2013\)](#)'s method.

## B Sensitivity Analysis

### B.1 Robustness Check — Alternative Measures of Labor Input

Table B.1: Robustness Check — Sectoral Home Bias and Productivity Effect

Dep. Var: Sectoral HB	( 1 )	( 2 )	( 3 )	( 4 )
TFP adjusted	-0.064 ***	-0.098 ***	-0.127 ***	-0.021 *
for human capital	( 0.012 )	( 0.013 )	( 0.014 )	( 0.013 )
and labor hours	[ -0.166 ]	[ -0.256 ]	[ -0.330 ]	[ -0.054 ]
Constant	0.366 ***	0.371 ***	0.200 ***	0.641 ***
	( 0.016 )	( 0.026 )	( 0.039 )	( 0.073 )
Country FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Sector FE	No	No	No	Yes
Observations	2,816	2,816	2,816	2,816
$R^2$	0.013	0.048	0.089	0.490

Note: Robust standard errors in parentheses and standardized coefficients in brackets.\*\*\*significant at 1%, \*\* at 5%, and \* at 10%. The dependent variable is dynamic sectoral home bias. The independent variable is dynamic sectoral TFP1 adjusted for differences in human capital and labor hours across countries. Country, sector, and time fixed effects are also considered in the regressions.

### B.2 Robustness Check — Alternative Parametrization

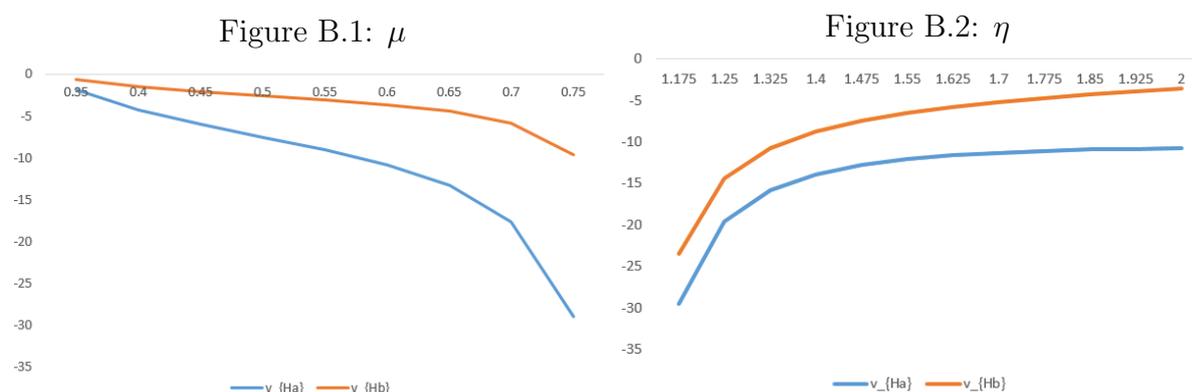
In this section, I examine the implications of alternative parameter values for portfolio choice in my model. In particular, I experiment with different  $\mu$  (share of domestic goods in consumption) and  $\eta$  (intra-sectoral elasticity of substitution) in household utility. The graphs below present numerical results.

In the first graph, holdings of domestic assets decrease in  $\mu$ , a measure of consump-

tion home bias. The intuition is that, the more a country consumes its own goods, the greater influence domestic productivity shocks exert on consumption levels. As a result, households hold fewer domestic assets and more foreign assets to hedge risks.

In the second graph, holdings of domestic assets increase in  $\eta$ , the elasticity of substitution between domestic and foreign goods. If consumers can easily switch between domestic and foreign goods without incurring significant utility loss, their consumption is less subject to domestic shocks. Therefore, they do not need to hold as many foreign assets to hedge risks.

In either case, domestic holdings are negative due to the labor income risk. Moreover, households hold fewer domestic assets in the more productive sector (sector  $a$ ) than in the less productive sectors (sector  $b$ ). So the results are qualitatively the same as in the benchmark case.



Note: This figure presents sectoral home bias under different values of the share of domestic goods in consumption  $\mu$  and intra-sectoral elasticity of substitution  $\eta$ . Parameter values of  $\mu$  and  $\eta$  are on the vertical axes and equity holdings are on the horizontal axes.