What Explains Equity Home Bias?
Theory and Evidence at the Sector Level

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Abstract

This paper examines the well-known home bias puzzle in international finance by exploiting the cross-sector variation. Using unique financial datasets, I calculate a sectoral home bias index that covers 27 industries in 43 countries, which enables empirical and theoretical analysis of the puzzle in unprecedented detail. The major empirical patterns include (1) sectoral home bias is stronger for non-tradable sectors and in countries with a higher degree of capital restrictions, and (2) investors tilt portfolios more towards domestic assets for the sectors in which their countries reveal a comparative advantage. Motivated by these findings, I build a multi-sector model that incorporates transaction costs, information asymmetry, and risk-hedging motives in investors’ portfolio choice. Moreover, I quantify the effects of these frictions on both sector- and country-level home bias in a calibrated DSGE model. This framework sheds light on the patterns and determinants of international financial investment.

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1 Introduction

Investors exhibit strong bias in favor of domestic equities, despite the current integration of global financial markets. This phenomenon of “equity home bias”, which contradicts the traditional theory of portfolio diversification, continues to be a famous puzzle in international finance. Existing literature on the subject has examined home bias at the country level, but little is known at the sector level about investors’ preference between domestic and foreign assets. This paper not only empirically and theoretically analyzes the sector-level home bias, but also evaluates competing explanations for the country-level home bias by exploiting the cross-sector variation.

In the literature there are two broad classes of explanations for equity home bias: financial frictions in global markets and risk-hedging by investors. The first explanation focuses on institutional transaction barriers and information frictions in global financial markets that may tilt portfolios toward domestic securities. The second explanation studies the relevance of correlation between asset returns and nontraded factors, including labor income and real exchange rate, for investors’ asset positions. Nevertheless, there is no unified theoretical framework or detailed sub-country data that allow economists to distinguish between the two explanations and disentangle their effects on portfolio non-diversification. This paper fills the gap in the literature by utilizing the variation across sectors, which enables examination of the patterns and determinants of equity home bias in unprecedented detail.

In the empirical section, I first describe the data and methodology employing which I construct the sectoral home bias index. 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 over the sample period from 1998 to 2014. The summary statistics of the index suggest that the share of foreign equities in investors’ portfolios is about 60 percent of what it should be based on the international CAPM averaged across countries and sectors. In the next step, I document empirical regularities of sectoral home bias by evaluating country, sector, and time effects respectively. I find that sectoral home bias is weaker in countries where financial openness, measured by the Chinn-Ito index, is greater.

1See Coeurdacier and Rey (2013) for a comprehensive survey on the topic. Papers that examine risk-hedging motives include Baxter and Jermann (1997), Cole and Obstfeld (1991), and Heathcote and Perri (2013). Meanwhile, Lewis (1999) and Brennan and Cao (1997) among others investigate the impact of institutional and information frictions on home bias. Investors’ behavioral biases driven by these market frictions can also be counted in this category (see, for example, French and Poterba (1991)).
This finding, complementing the national evidence found by Lewis (1999) and Lane and Milesi-Ferretti (2003), indicates that institutional frictions constrain international diversification. Moreover, I find that investors show stronger home bias in nontradable sectors than in tradable sectors.\(^2\) This novel evidence supports the theoretical arguments made by Stockman and Dellas (1989) and Obstfeld and Rogoff (2001) that nontradable sectors can potentially induce home bias, since risk-hedging investors may prefer to hold domestic assets, particularly domestic nontradable sector assets, to stabilize purchasing power under the fluctuation of real exchange rates. Lastly, I find that sectoral home bias declined over time during the sample period, consistent with the empirical pattern documented by Coeurdacier and Rey (2013) at the country level.

In addition to these factors proposed by the existing literature, I hypothesize and then confirm that relative sectoral productivity measured by comparative advantage is a crucial determinant of sectoral home bias. Sectors with different productivity levels potentially expose investors to risks of different magnitudes, which lead investors to exhibit distinct preference for domestic versus foreign assets across sectors. Moreover, investors are subject to information frictions of varying degrees across sectors depending on which sectors their country relatively excel in. These two factors can jointly decide how comparative advantage shapes the pattern of sectoral home bias. In the empirical analysis, I find that sectoral home bias positively comoves with the measure of revealed comparative advantage, which suggests that investors tilt portfolios more towards domestic assets for the sectors in which their countries reveal a comparative advantage. This finding implies that sectors are subject to different levels of frictions which covary with sectoral productivity. Exploiting this cross-sector heterogeneity enriches the understanding of the home bias puzzle.

Motivated by these empirical findings, I develop a symmetric two-country two-sector DSGE model in the theory section to elucidate the effects of various frictions on sectoral home bias. In particular, the model incorporates relative sectoral productivity, asset transaction costs, and information frictions. Asset transaction costs are assumed to be an iceberg cost on foreign asset returns, similar to the specification in Heathcote and Perri (2004) and Tille and Van Wincoop (2010). Information frictions are modeled as a higher perceived variance of foreign assets following the literature including Brenman and Cao (1997) and Okawa and Van Wincoop (2012). To obtain the solution to the portfolio choice problem, I follow the perturbation method developed by Devereux and Sutherland

\(^2\)In the sample, tradable sectors include manufacturing and transportation, while nontradable sectors include services, construction and utilities.
(2011), who combine a second-order approximation of Euler equations with a first-order approximation of the other equations of the model in order to determine a steady-state portfolio. The methodological contribution I make is to modify the original method in order to accommodate the two types of financial frictions and examine how they affect investors’ asset positions.

The theoretical predictions from the model confirm that institutional and informational frictions are important contributors to home bias. Moreover, I also find that sectoral home bias is stronger in comparative disadvantage sectors. This result is driven by investors’ incentives to avoid domestic productive sectors for risk hedging. However, if there exist asset transaction costs or information frictions, investors are more likely to show stronger home bias in comparative advantage sectors. This finding implies that these two market frictions dominate investors’ risk-hedging motives in driving investors’ asset positions. This theoretical result can potentially explain the empirical finding on the positive comovement between revealed comparative advantage and sectoral home bias.

To quantify the magnitude of each friction in the real world, I conduct a quantitative assessment of an extended model that covers a large group of countries and sectors. In this extended model, I employ the trade framework developed by Eaton and Kortum (2002), which embodies the Ricardian theory of comparative advantage. In terms of the computation strategy, the real side of the economy, including sectoral productivity and trade costs in the goods market, is calibrated to match a country’s trade flows with the rest of the world. The financial side of the economy, including asset transaction costs and information frictions, is calibrated to match a country’s national as well as sectoral home bias. After estimating these variables, I conduct a series of counterfactual analyses in which I exclude one friction at a time and examine how home bias changes. These counterfactual exercises allow me to disentangle the contribution of each friction to equity home bias. Based on the numerical results, asset transaction costs are more critical than information frictions in explaining sectoral home bias. Furthermore, investors’ risk-hedging motives remain to be important drivers for national home bias.

This paper contributes to the asset home bias literature by providing novel empirical and theoretical results at the sector level. By exploiting the cross-sector variation, it enables examination of the puzzle in detail with a unified framework that encompasses various explanations for the home bias puzzle. As is surveyed by Coeurdacier and Rey (2013), economists have proposed market frictions such as transaction barriers (see, for example, French and Poterba (1991) and Lewis (1999)) and information frictions (see Brennan and Cao (1997), Portes et al. (2001), Ahearne et al. (2004), Massa
and Simonov (2006), Van Nieuwerburgh and Veldkamp (2009), Okawa and Van Wincoop (2012) among others) as determinants for investors’ portfolio choice among global assets. Others have examined the risk-hedging motives that cause deviation of investors’ asset positions from perfect diversification. This strand of literature can be further divided into papers that focus on labor income risk (Baxter and Jermann (1997), Baxter et al. (1998), and Heathcote and Perri (2013), etc) and those on real exchange rate risk (Stockman and Dellas (1989), Kollmann (2006), Matsumoto (2007), and Coeurdacier (2009), etc). These theoretical papers study one potential explanation mainly due to the scarcity of data even at the country level that allows economists to discriminate and disentangle multiple factors. In addition, most of these papers see a country as a whole and therefore ignore sectoral heterogeneity. As argued in Hu (2020), investors are able to hedge their risk 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). Therefore, acknowledging sectoral heterogeneity by developing a multi-sector framework enriches our understanding of investors’ risk-hedging pattern and portfolio choice.

Besides this paper, Schumacher (2018) and Agarwal et al. (2020) also use asset holding data to examine institutional investors’ portfolio choices at the sector level. These two empirical papers focus on investors’ preference among foreign securities, while I attack the home bias puzzle by investigating the determinants of investors’ choice between domestic and foreign assets. Last but not least, this paper is related to the literature on the interaction of risk-sharing and industrial specialization led by Helpman and Razin (1978), Kalemli-Ozcan et al. (2003), and Koren (2003). The framework developed in this paper can be used to study how trade specialization shaped by comparative advantage influences portfolio diversification. These works on the interplay of capital and commodity flows are essential for understanding the patterns of globalization.

The remainder of the paper proceeds as follows: Section 2 describes the data and method used to compute sectoral home bias and presents its empirical regularities. Section 3 develops a two-country two-sector model to illustrate the importance of various frictions in explaining home bias. Section 4 quantifies the magnitude and impact of the frictions in a calibrated quantitative framework. Section 5 concludes.
2 Empirical Analysis

In this section, I first detail the method and data used to construct the sectoral home bias index. After that, I explore the country-, sector-, and time-specific factors that explain its variation. Moreover, I empirically establish its relation with sectoral productivity measured by revealed comparative advantage. These novel empirical findings at the sectoral level enable me to examine the patterns and determinants of equity home bias in detail.

2.1 Constructing Sectoral Home Bias Index

To construct the home bias index, I follow Coeurdacier and Rey (2013) by using the difference between the holdings of equities and the share of market capitalization in the global equity market. This difference reflects the deviation of data from the international CAPM, which 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 adapt the method to sector-level analysis, which suggests that home bias in country \(i\) sector \(s\) at time \(t\) is defined as

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

The numerator in the formula uses data from Factset/Lionshare, while the denominator uses market values from Datastream.

Factset/Lionshare provides comprehensive data on the equity holdings of institutional investors from a large group of countries since 1998. Typical institutional investors include banks, insurance companies, retirement or pension funds, hedge funds, and sovereign wealth funds. 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 worldwide, and company annual reports.

I use institutional investors’ holdings as a proxy for the whole country’s portfolio choice for the following reasons. First, information on household portfolio is scarce, leaving institutional investors as the only subject whose portfolio distribution across sectors and countries can be studied. Second, the country-level home bias index constructed with the Factset/Lionshar 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.2). This consistency shows that the under-representation problem caused by considering institutional investors only will not bias the results significantly. Third, institutional investors have replaced households as the main player in equity markets worldwide. Figure A.3 shows how the household share of equity ownership in the U.S. has significantly declined 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. Therefore, the investment strategies of financial institutions are crucial for understanding the pattern of global financial flows.

However, two limitations of using the Factset/Lionshare data to compute home bias are worth noting. In particular, institutional investors may not only represent the households of their origin. This is especially the case for the countries with low tax rates which attract foreign households. Moreover, securities of foreign multinationals cannot be distinguished directly from domestic securities in the Factset/Lionshare dataset. As is argued by Rowland and Tesar (2004), holding multinationals’ securities in the domestic market is similar to holding securities in the foreign market for diversification purposes. These two data limitations can be addressed by including dummies for tax havens and major financial hubs hosting multinationals, but the coding of the two dummies can be subjective. Alternatively, I control for country fixed effects in the regressions to confirm the robustness of the empirical findings despite the data limitations.

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

Combining all the data, I compile the annual sectoral home bias index using formula 1. The index covers 27 sectors in 43 countries over the sample period from 1998 to 2014.

\[^3\text{For instance, institutions accounted for 88 percent of the ownership of EU corporate equities in 2012, according to the INSEAD OEE Data Services.}\]
(see table A.2 for a list of countries and sectors in the sample). Figure 1 shows the histogram of sectoral home bias averaged over time. Let $\bar{HB}_{i,s}$ denote the time-averaged home bias of country $i$ sector $s$. $\bar{HB}_{i,s} = 1$ indicates complete home bias for sector $s$ in country $i$, since it does not hold any foreign equities $s$ since it does not hold any foreign equities. $\bar{HB}_{i,s} = 0$ indicates that country $i$ is fully diversified. In theory, $\bar{HB}_{i,s}$ can take any value equal to or smaller than 1 (including negative values). When the value is negative, it means that the country over-invests in foreign equities relative to market shares of the sector. There are 834 observations in the histogram, with mean and standard deviation equal to 0.42 and 0.36, respectively. The index ranges from -0.18 to 1, with many observations clustered around 0 and 1, representing the case with no home bias and complete home bias respectively. The median value of 0.36 suggests that the share of foreign equities in investors’ portfolios is about 64 percent of what it should be according to the international CAPM. Figure A.4 reports the U.K. sectoral home bias as an example. The mean value is 0.28 and the standard deviation is 0.17. Publishing and hospitality show the strongest home bias, while the iron and steel industry shows the weakest.

As both figures 1 and A.4 suggest, there is significant variation in the degree to which investors prefer domestic equities across sectors and countries. In the next step, I investigate various determinants of sectoral home bias to explore the factors influencing investors’ portfolio choices in the global financial market.

### 2.2 Determinants of Sectoral Home Bias

In this section, I explore the country-, sector-, time-specific factors that potentially influence portfolios according to the existing literature on country-level home bias. The comprehensive sector-level panel data in my sample allows me to examine the impact of these factors in unprecedented detail.

At the country level, one of the most notable contributors to national home bias is asset transaction costs in global financial markets (see French and Poterba (1991) and Coeurdacier and Rey (2013)). Such costs, including capital controls and differences in trading costs or tax treatments between domestic and foreign assets, lower investors’ ability and motivation to hold foreign assets. These country-level barriers that impair global financial mobility should also help explain home bias at the sector level. Therefore,

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4I exclude the sectors whose holding data are missing from Factset/Lionshare, hence not every country has entries for all the 27 industries.
I use the Chinn-Ito index as a proxy for financial openness when exploring sectoral home bias determinants. 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. The higher the index value, the lower asset transaction costs a country’s investors face when investing abroad.

At the sector level, economists including Stockman and Dellas (1989) and Tesar (1993) contend that since households are exposed to fluctuations in the relative price of nontradable sectors, they may skew their portfolio towards domestic assets, especially domestic nontradable sectors’ assets to hedge risks. In particular, Obstfeld and Rogoff (2001) reason that in the case where tradable and nontradable consumption are log-separable in utility, households should hold globally diversified assets of tradable sectors and only domestic assets of nontradable sectors. While theoretical work is abundant, empirical work examining whether investors show more substantial home bias in nontradable sectors is missing. This paper addresses this gap by analyzing home bias at the sector level. When categorizing industries into tradable and nontradable sectors, I follow the benchmark
Table 1: Determinants of Sectoral Home Bias

<table>
<thead>
<tr>
<th>Dep. Var: Sectoral HB</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chinn-Ito</td>
<td>-0.688 ***</td>
<td>-0.238 ***</td>
<td></td>
<td>(0.013)</td>
<td>(0.036)</td>
<td>(0.072)</td>
</tr>
<tr>
<td></td>
<td>[0.444]</td>
<td>[0.153]</td>
<td></td>
<td>[-0.175]</td>
<td>[-0.153]</td>
<td>[-0.072]</td>
</tr>
<tr>
<td>Tradable dummy</td>
<td>-0.050 ***</td>
<td>-0.065 ***</td>
<td>-0.062 ***</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td></td>
<td>[-0.127]</td>
<td>[-0.166]</td>
<td>[-0.175]</td>
<td>[-0.153]</td>
<td>[-0.166]</td>
<td>[-0.160]</td>
</tr>
<tr>
<td>Year</td>
<td>-0.006 ***</td>
<td>-0.006 ***</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td></td>
<td>[-0.016]</td>
<td>[-0.016]</td>
<td>[-0.016]</td>
<td>[-0.016]</td>
<td>[-0.016]</td>
<td>[-0.016]</td>
</tr>
<tr>
<td>Country FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Sector FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Year FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Observations</td>
<td>11,795</td>
<td>11,795</td>
<td>11,795</td>
<td>11,795</td>
<td>11,795</td>
<td>11,795</td>
</tr>
<tr>
<td>R²</td>
<td>0.197</td>
<td>0.531</td>
<td>0.004</td>
<td>0.509</td>
<td>0.542</td>
<td>0.515</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, standardized coefficients in brackets. *** significant at 1%. The dependent variable is sectoral home bias, the independent variables include the Chinn-Ito index for financial openness, a dummy for tradable sectors, the year in which data are observed, and country, sector, time fixed effects.

In terms of time-series variation, country-level home bias has declined over the past several decades, as is documented by Coeurdacier and Rey (2013). A combination of factors such as reductions in asset transaction costs and informational asymmetries, as well as advanced trading technology in the financial industry, can potentially explain this downward trend. With the available comprehensive panel data, I can examine whether the phenomenon of home bias is indeed disappearing across countries and sectors.

Table 1 presents the findings on the determinants of sectoral home bias discussed above. Columns (1) and (2) show that countries with a higher degree of financial openness, as measured by the Chinn-Ito index, exhibit weaker sectoral home bias. In particular, Column (2) suggests that when country, sector, and time fixed effects are controlled for, a 1 standard deviation increase in financial openness is associated with a .153 standard deviations decrease in sectoral home bias. This result that investors from economies with more financial openness hold a larger share of foreign assets at the sector level is used by Mano and Castillo (2015), who classify industries’ tradability based on the trade data. More specifically, manufacturing and transportation (industries coded 1-15 and 20-22 in table A.2) are tradable sectors. Services, construction, and utilities (industries coded 16-19 and 23-27 in table A.2) are nontradable sectors. In addition to the dummy variable, I construct a continuous measure of sectoral tradability based on the World Input-Output Database to verify the robustness of the findings.
consistent with the country-level observations documented by French and Poterba (1991) and Coeurdacier and Rey (2013).

Columns (3) and (4) in table 1 report the correlation between sectoral home bias and a tradable dummy whose value equals 1 for tradable sectors and 0 for nontradable sectors. Based on the standardized coefficient in column (4), home bias in tradable sectors is 0.166 standard deviations lower than in nontradable sectors, when country and time fixed effects are controlled for. Table C.1 confirms that the result is robust under a continuous measure of tradability. This novel empirical result that home bias is stronger in the nontradable sector resonates with the theoretical arguments made by Stockman and Dellas (1989), Tesar (1993), and Obstfeld and Rogoff (2001). While these papers focus on hedging real exchange rate fluctuations, there may exist other potential explanations for the difference in home bias between tradables and nontradables. For instance, households face higher information frictions in nontradables since they acquire more knowledge about tradables through imports. I will distinguish between risk-hedging motives and information frictions as drivers of variation in sectoral home bias in the quantitative model.

Lastly, columns (5) and (6) document that sectoral home bias has declined over time. During the sample period, sectoral home bias decreases by .016 standard deviations annually. This declining pattern is consistent with that for national home bias found by Lane and Milesi-Ferretti (2003) and Coeurdacier and Rey (2013). In addition to this baseline result, I conduct robustness checks by including the interaction terms of time effects with other factors. As is shown in table C.2, the decline in sectoral home bias is especially pronounced in financially-open countries and for tradable sectors. This result suggests the existence of frictions that prohibit foreign investment in nontradable sectors and in economies with capital restrictions, which prevent investors from reaping the diversification benefits through holdings of foreign assets.

To sum up, sectoral home bias is weaker in countries with higher financial openness, for tradable sectors, and more so in the recent past. These findings complement existing theoretical and empirical papers on national home bias.

2.3 Sectoral Home Bias and Comparative Advantage

In addition to the contributors to home bias identified by the existing literature, the interaction among country, sector, and time factors also influence investors’ portfolio choice. Among these factors, I hypothesize that relative sectoral productivity measured
as comparative advantage is a crucial determinant of sectoral home bias.

The economic reasoning behind this hypothesis is that domestic sectors with different productivity levels can potentially expose investors to risks of heterogeneous magnitudes, which lead investors to exhibit distinct preference for domestic assets across sectors. As is surveyed by Coeurdacier and Rey (2013), the literature summarizes two sources of risks that may skew investors’ portfolios under their risk-hedging incentives. First, ‘labor income risk’ arises from the fluctuation in human capital income (see Baxter and Jermann (1997), Heathcote and Perri (2013), etc). Second, ‘real exchange rate risk’ refers to the fluctuation in households’ purchasing power due to the changes in goods’ prices (see Matsumoto (2007), Coeurdacier (2009), etc). These two factors cannot be traded in financial markets, which induce investors to consider their comovements with available financial assets when constructing portfolios.

In a multi-sector framework, a sector with greater comparative advantage is potentially associated with higher labor income 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. This is driven by the fact that more productive sectors tend to have a larger influence on the aggregate economy since they export more goods and create more jobs. When these sectors fail, the whole country suffers drastic labor income losses. If investors hold many home assets in these sectors, their labor income and financial income may plummet simultaneously. Therefore, to hedge against labor income fluctuations, it is optimal for investors to hold fewer home assets in comparative advantage sectors and hence show weaker sectoral home bias.

Similarly, a comparative advantage sector can also be associated with greater real exchange rate risk since its returns negatively correlate with the domestic price level. Consider the sector experiences a negative productivity shock, and hence its financial returns fall. Meanwhile, its output price increases to clear the goods market, which — given its greater weight in the price level under comparative advantage — can lead to the appreciation of the real exchange rate. Therefore, holding home assets in such a sector is not optimal for risk-hedging purposes, given the negative correlation between the financial return and real exchange rate. Instead, if households hold financial assets whose returns increase when domestic price levels rise, they do not need to significantly compromise consumption when local goods become more expensive, since the shortfall in purchasing power can be partially offset by their increased financial income.

To empirically test these risk-hedging hypotheses, I compile the sectoral financial return index available from Datastream and examine its correlation with countries’ la-
bor income and real exchange rate. The country-level labor income data are obtained from Karabarbounis and Neiman (2013), and the CPI-based real effective exchange rate (REER) data are constructed by the IMF.\(^5\) To examine whether sectors with greater comparative advantage are exposed to higher labor income risk and real exchange rate risk, I conduct a two-step analysis. In the first step, I calculate the correlation between sectoral financial return and national labor income as well as the correlation between sectoral financial return and real exchange rate. In the second step, I test whether the correlations covary with sectoral comparative advantage.

Following the trade literature, I employ Balassa (1965)’s method to construct a measure of revealed comparative advantage (RCA hereafter). The measure is based on the Ricardian trade theory: a country reveals a comparative advantage when it is a competitive producer and exporter of that sector relative to the world average. Based on this idea, RCA is defined as

\[
RCA_{i,s,t} = \frac{X_{i,s,t}}{\sum_{s=1}^{S} X_{i,s,t}} \times \frac{X_{w,s,t}}{\sum_{s=1}^{S} X_{w,s,t}},
\]

where \(X_{i,s,t}(X_{w,s,t})\) denotes country \(i\)’s (world’s) exports of sector \(s\) at time \(t\). To compute RCA, I use the UN Comtrade dataset at the 3- and 4-digit ISIC levels corresponding to the sectors that appear in Factset/Lionshare and Datastream (table A.3). I then use the time-averaged RCA in country \(i\) sector \(s\) denoted as \(\bar{RCA}_{i,s}\) as the independent variable in the second step, whose regression results are presented in table 2. Based on the estimated coefficients, even though the negative correlation between financial returns and real exchange rate is not significant, the returns to comparative advantage sectors are more highly correlated with domestic labor income. This positive comovement makes it optimal for households to hold fewer home assets in these sectors for risk-hedging purposes.

After confirming the risk-hedging benefits of avoiding home assets in comparative advantage sectors, I examine whether investors follow this optimal strategy by exhibiting weaker home bias in these sectors. To this end, I explore the relationship between sectoral home bias and RCA and report the results in table 3. Contrary to the expectation, the data suggest that home bias increases in RCA, which implies that investors reveal a stronger home bias in comparative advantage sectors. As column (4) in table 3

\(^5\)The country-level labor income is the product of total labor share (TSL) and GDP in Karabarbounis and Neiman (2013)’s dataset. The CPI-based REER is the product of nominal exchange rate and relative price levels, weighted across a country’s trading partners. An increase in REER means an appreciation of the country’s real exchange rate relative to a basket of other currencies.
Table 2: RCA and risk-hedging

<table>
<thead>
<tr>
<th></th>
<th>$\rho(r_{i,s}, w_i L_i)$</th>
<th>$\rho(r_{i,s}, e_i)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RCA_{i,s}$</td>
<td>0.019 *</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>( 0.011 )</td>
<td>( 0.013 )</td>
</tr>
<tr>
<td>Country FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Sector FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>408</td>
<td>360</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.260</td>
<td>0.509</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, *significant at 10%. The dependent variable is the correlation between sectoral asset returns $r_{i,s}$ and national labor income $w_i L_i$ as well as real exchange rates $e_i$. The independent variables include $RCA_{i,s}$ which is sectoral revealed comparative advantage averaged over the sample period, and country and sector fixed effects.

Table 3: Sectoral home bias and revealed comparative advantage

<table>
<thead>
<tr>
<th>Dep. Var: Sectoral HB</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCA</td>
<td>0.015 ***</td>
<td>0.017 ***</td>
<td>0.021 ***</td>
<td>0.021 ***</td>
</tr>
<tr>
<td></td>
<td>( 0.003 )</td>
<td>( 0.003 )</td>
<td>( 0.003 )</td>
<td>( 0.003 )</td>
</tr>
<tr>
<td></td>
<td>[ 0.061 ]</td>
<td>[ 0.071 ]</td>
<td>[ 0.085 ]</td>
<td>[ 0.083 ]</td>
</tr>
<tr>
<td>Chinn-Ito</td>
<td>-0.760 ***</td>
<td>-0.194 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( 0.018 )</td>
<td>( 0.056 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[ -0.484 ]</td>
<td>[ -0.123 ]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Sector FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
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<td>Year FE</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>6,064</td>
<td>6,064</td>
<td>6,064</td>
<td>6,064</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.004</td>
<td>0.237</td>
<td>0.564</td>
<td>0.566</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, standardized coefficients in brackets. ***significant at 1%. The dependent variable is sectoral home bias. The independent variables include sectoral revealed comparative advantage $RCA_{i,s,t}$, Chinn-Ito index, and country, sector, time fixed effects.

suggests, when RCA increases by 1 standard deviation, sectoral home bias increases by 0.083 standard deviations. The positive comovement between the two variables remains economically and statistically robust under various configurations of fixed effects.

This analysis, by exploiting the variation in sectoral risk exposure and home bias, casts doubt on the importance of risk-hedging motives in explaining investors’ portfolio choice. Even at the country level, economists find the empirical evidence supporting the theory to be mixed. For example, Wincoop and Warnock (2008) and Massa and Simonov (2006) find the correlation between financial returns and non-traded factors (real exchange rates and labor income) to be too low to rationalize home bias through risk-hedging. This sector-level analysis complements these papers by using more detailed data.
One potential explanation to address the discrepancy between the theoretical hypothesis and the empirical finding is that there exists another friction, which works against and eventually dominates risk-hedging incentives by skewing portfolios towards riskier assets representing domestic comparative advantage sectors. Information friction, which has been well established in the home bias literature, can potentially be such a friction. If information asymmetry between domestic and foreign assets is exacerbated in comparative advantage sectors, investors are more likely to exhibit stronger home bias for these sectors. For example, Korea has a comparative advantage in the electronics industry; therefore, Korean households are knowledgeable about domestic companies like Samsung and LG. Nevertheless, the strength in the industry may dampen Koreans’ motivation to inquire into foreign companies such as Apple. It also reduces opportunities for Korean households to acquire knowledge about foreign companies through imports. Through this lens, a comparative advantage sector is subject to greater information frictions. This reasoning can potentially explain why investors would show stronger home bias for comparative advantage sectors even though these sectors expose them to greater risks. However, whether the information friction is relevant for sectoral home bias is hard to test empirically due to the lack of proxies for information frictions at the sector level. Therefore, we need a theoretical model in which we can disentangle the frictions and quantify their relevance.

### 3 Theory

Motivated by the empirical findings, I build a symmetric two-country two-sector illustrative model to elucidate the effects of nontraded factors (labor income and real exchange rate), transaction costs, and information frictions on equity home bias.

---

6Empirical evidence found by Ahearne et al. (2004) and Bae et al. (2008) among others suggests the existence of the information barriers investors face when buying foreign assets. On the theoretical front, Brennan and Cao (1997) and Okawa and Van Wincoop (2012) model the friction as an exogenous information set with investors’ higher perceived variance for foreign assets, while Van Nieuwerburgh and Veldkamp (2009) endogenize the information acquisition decision to examine the home bias puzzle.

7Behavioral biases driven by asymmetric expectations and beliefs (see French and Poterba (1991) and Dumas et al. (2009) among others) work similarly. Empirically it will be challenging to disentangle them from information frictions though.

8At the country level, economists have used geographic distance (Portes et al. (2001)) or cross-listing companies’ market share (Ahearne et al. (2004)) as an indicator for information frictions. But there lacks comprehensive cross-country measure at the sector level which approximates information frictions but does not covary with risk-hedging factors such as trade volume.
3.1 Setup

Two symmetric countries \((i \in \{H, F\})\) both produce two types of tradable consumption goods \((s \in \{a, b\})\). Production in country \(i\) sector \(s\) combines labor \(l_{i,s,t}\) and capital \(k_{i,s,t}\) endowments in a Cobb-Douglas function

\[
y_{i,s,t} = T_{i,s,t} k_{i,s,t}^{\alpha} l_{i,s,t}^{1-\alpha},
\]

where productivity \(T_{i,s,t}\) follows an AR(1) process over time with an autoregressive coefficient \(\rho_{i,s}\) and a long-term mean \(\bar{T}_{i,s}\):

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

Productivity innovations are assumed to be i.i.d. shocks \(\epsilon_{i,s,t} \sim N(0, \sigma_{\epsilon}^2)\) in the baseline case. In the quantitative model, their covariance matrix \(\Sigma\) incorporating within- and cross-country correlations will be estimated from the data.

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, which also reflects the degree of comparative advantage.

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:

\[
d_{i,s,t} = \alpha p_{i,s,t} y_{i,s,t},
\]

where \(p_{i,s,t}\) denotes the price of output in country \(i\) sector \(s\).

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

\[
E_0 \sum_{t=0}^{\infty} \beta^t \frac{C_{i,t}^{1-\sigma}}{1-\sigma}.
\]
Consumption is a constant-elasticity-of-substitution (CES) bundle of \( a \) and \( b \) goods:

\[
C_{i,t} = \left( \psi_i \phi_{i,a,t} + (1 - \psi_i) \phi_{i,b,t} \right)^{\frac{1}{\phi - 1}},
\]

where \( \psi_i \) is country \( i \)’s expenditure share on sector \( a \) and \( \phi \) is the elasticity of substitution between sectors. Therefore, the price level in country \( i \) is

\[
P_{i,t} = \left( \psi_i P_{i,a,t}^{1-\phi} + (1 - \psi_i) P_{i,b,t}^{1-\phi} \right)^{\frac{1}{\phi - 1}},
\]

whose cross-country ratio defines the real exchange rate

\[
e_t = \frac{P_{H,t}}{P_{F,t}}.
\]

Within each sector \( s \), consumption is another CES bundle of goods produced at home and abroad, with its quantity and price given by:

\[
C_{i,s,t} = \left( \mu_i \eta_{i,s,t} + (1 - \mu_i) \eta_{j,s,t} \right)^{\frac{1}{\eta - 1}},
\]

\[
P_{i,s,t} = \left( \mu_i p_{i,s,t}^{1-\eta} + (1 - \mu_i) p_{j,s,t}^{1-\eta} \right)^{\frac{1}{1-\eta}},
\]

where \( C_{i,s,t} (C_{j,s,t}) \) is the consumption of domestic (imported) goods and \( \eta \) denotes the elasticity of substitution within sectors. If domestic goods account for more than half of the consumption \( (\mu_i > \frac{1}{2}) \), countries exhibit consumption home bias. Consumption preference is assumed to be symmetric in the baseline case such that \( \psi_H = 1 - \psi_F, \mu_H = \mu_F \).

In the factor market, wage \( w_{i,t} \) and capital rental fee \( r_{i,t} \) are determined by the market clearing conditions for factor endowments:

\[
l_{i,a,t} + l_{i,b,t} = \bar{L}_i, \quad k_{i,a,t} + k_{i,b,t} = \bar{K}_i, \quad i \in \{ H, F \}.
\]

The endowments are mobile within a country but immobile across borders. In the labor market, I normalize the number of households to one in each country and assume a household supplies one unit of labor inelastically for simplicity.

In the stock market, a household purchases equities of country \( i \) sector \( s \) at time \( t \) for price \( q_{i,s,t} \). Let \( \nu_{i,s,t} (\nu_{i,s,t}^\circ) \) denote the number of shares \( H \) (\( F \)) country’s household holds for sector \( s \) from country \( i \) at time \( t \), then the budget constraints of households in country \( H \) and \( F \), given by equations 14 and 15 respectively, state that the sum of
consumption expenditures and changes in asset positions is equal to the sum of labor income and dividend income:

\[
P_{H,t}C_{H,t} + \sum_{s=\{a,b\}} [q_{H,s,t}(\nu_{H,s,t+1} - \nu_{H,s,t}) + q_{F,s,t}(\nu_{F,s,t+1} - \nu_{F,s,t})] = w_{H,t}\bar{L}_H + \sum_{s=\{a,b\}} (d_{H,s,t}\nu_{H,s,t} + d_{F,s,t}\nu_{F,s,t}),
\]

(14)

\[
P_{F,t}C_{F,t} + \sum_{s=\{a,b\}} [q_{H,s,t}(\nu_{H,s,t+1} - \nu_{H,s,t}) + q_{F,s,t}(\nu_{F,s,t+1} - \nu_{F,s,t})] = w_{F,t}\bar{L}_F + \sum_{s=\{a,b\}} (d_{H,s,t}\nu_{H,s,t} + d_{F,s,t}\nu_{F,s,t}).
\]

(15)

I introduce two financial market frictions into the model. The first one is asset transaction costs, modeled as a repatriating tax on foreign returns similar to Heathcote and Perri (2004) and Tille and Van Wincoop (2010). Given the iceberg cost denoted as \(\tau_i\), when country \(i\)’s investors earn 1 unit of wealth from investing abroad, they can only collect \(1 - \tau_i\) units.\(^9\) The transaction costs are assumed to be second-order in magnitude, which implies that they are proportional to the variance of asset returns. The other friction is the information friction, which is modeled as a higher perceived variance of foreign assets following Brennan and Cao (1997), Van Nieuwerburgh and Veldkamp (2009), and Okawa and Van Wincoop (2012) among others. The idea is that investors perceive foreign stocks as riskier and reduce their foreign stock holdings accordingly. In the model I assume information frictions, denoted as \(\tilde{f}_{ij,s}\), are proportional to the variance of sectoral productivity shocks \(\sigma^2_{i,s}\), such that from the perspective of households in country \(j\), \(\epsilon_{i,s}\) has a mean of 0 and variance \(\tilde{f}_{ij,s}\sigma^2_{i,s}\). In this symmetric case, \(\tilde{f}_{ii,s} = \tilde{f}_{jj,s} = 1\), \(\tilde{f}_{ij,s} = \tilde{f}_{ji,s} = \tilde{f}_s > 1\). The information friction can be different across sectors, since the knowledge households acquire about foreign productivity may potentially vary with sector-specific factors such as sectoral trade volume.

The financial returns of country \(i\) sector \(s\) include dividends and capital gains:

\[
R_{i,s,t} = \frac{q_{i,s,t} + d_{i,s,t}}{q_{i,s,t-1}},
\]

(16)

\(^9\)The iceberg cost is assumed to be country-specific and therefore does not vary across sectors within a country. In reality, there could exist within-country variations for asset transaction barriers, particularly for sensitive industries like aerospace and defense. Such sectors, due to limited data coverage for them in Factset/Lionshare, Datastream, and UN Comtrade, are excluded from the empirical and quantitative analysis.
which influence households’ intertemporal decisions that yield Euler equations:

\[
\frac{U'(C_{i,t})}{P_{i,t}} = E_t[\beta \frac{U'(C_{i,t+1})}{P_{i,t+1}} \tilde{R}_{i',s,t+1}], \quad i, i' \in \{H, F\}; \quad s \in \{a, b\},
\]

where \(\tilde{R}_{i',s,t+1}\) denotes the asset returns \(R_{i,s,t+1}\) defined in equation 16 augmented with transaction costs and information frictions depending on whether the asset is domestic: \(\tilde{R}_{i',s,t+1} = R_{i',s,t+1}\) if \(i = i'\).

To sum up the description of the model setup, the equilibrium of the model consists of a set of prices and quantities such that 1) households choose consumption and construct portfolio to maximize their expected lifetime utility, 2) firms maximize their profits, and 3) factor, commodity, and asset markets clear.

### 3.2 Portfolio Choice

#### 3.2.1 Methodology and Parametrization

To solve for portfolios in the equilibrium of the economy, I employ Devereux and Sutherland (2011)’s perturbation method. Acknowledging that assets are only distinguishable by their risk characteristics, Devereux and Sutherland (2011) develop a method that combines a second-order approximation of Euler equations with a first-order approximation of the other equations of the model in order to determine a zero-order (i.e. steady-state) portfolio. This method has been widely used in deriving portfolios in open economy macro models.

The methodological contribution I make is to modify the original method in order to accommodate the financial frictions in this model. When households incur transaction costs \(\tau\) when repatriating foreign returns, it follows from Euler equations (17) that

\[
E_t[\frac{U'(C_{H,t+1})}{P_{H,t+1}} R_{H,s,t+1}] = E_t[\frac{U'(C_{H,t+1})}{P_{H,t+1}} (1 - \tau) R_{F,s,t+1}],
\]

\[
E_t[\frac{U'(C_{F,t+1})}{P_{F,t+1}} R_{F,s,t+1}] = E_t[\frac{U'(C_{F,t+1})}{P_{F,t+1}} (1 - \tau) R_{H,s,t+1}], \quad s \in \{a, b\}.
\]

In the two-country two-sector case, let \(R_{F,b,t}\) be a numeraire asset and \(\hat{R}_x\) denote the vector of excess returns to the other assets:

\[
\hat{R}_x = [\hat{R}_{H,a} - \hat{R}_{F,b}, \hat{R}_{H,b} - \hat{R}_{F,b}, \hat{R}_{F,a} - \hat{R}_{F,b}],
\]

where \(\hat{y}\) represents the log-deviation of any variable \(y\) from its steady state.

18
Based on the ordering of the assets in $R_x$, I introduce the vector of transaction costs defined as
\[ T = [\tau, \tau, 0], \tag{20} \]
which appears in the second-order Taylor expansion of Euler equations in both countries:
\[
\begin{align*}
E_t[\hat{R}_{x,t+1} + \frac{1}{2} \hat{R}^2_{x,t+1} + \frac{1}{2} T - (\sigma \hat{C}_{H,t+1} + \hat{P}_{H,t+1})\hat{R}_{x,t+1}] &= O(\epsilon^3), \\
E_t[\hat{R}_{x,t+1} + \frac{1}{2} \hat{R}^2_{x,t+1} - \frac{1}{2} T - (\sigma \hat{C}_{F,t+1} + \hat{P}_{F,t+1})\hat{R}_{x,t+1}] &= O(\epsilon^3). \tag{21}
\end{align*}
\]
Here $O(\epsilon^3)$ captures all terms of order higher than two, and $\hat{R}^2_{x,t+1}$ denotes differences in squared changes of returns
\[
\hat{R}^2_{x,t+1} = [\hat{R}^2_{H,a,t+1} - \hat{R}^2_{F,b,t+1}, \hat{R}^2_{H,b,t+1} - \hat{R}^2_{F,a,t+1}, \hat{R}^2_{F,a,t+1} - \hat{R}^2_{F,b,t+1}]. \tag{22}
\]
Taking the difference between the two equations in (21) yields a portfolio determination condition:
\[
E_t[(\hat{C}_{H,t+1} - \hat{C}_{F,t+1} + \frac{\epsilon_{t+1}}{\sigma})\hat{R}_{x,t+1}] = \frac{T}{\sigma} + O(\epsilon^3). \tag{23}
\]
On the left hand side of this portfolio determination condition are two components: 1) the cross-country consumption differential adjusted for the real exchange rate and 2) the excess returns to financial assets. In order to solve the portfolio choice problem, one needs to express these two components in terms of the innovations in the model
\[
\epsilon'_t = [\epsilon_{H,a,t}, \epsilon_{H,b,t}, \epsilon_{F,a,t}, \epsilon_{F,b,t}], \tag{24}
\]
whose coefficients as a function of asset positions, denoted as $\check{\alpha}' = [\check{\alpha}_{H,a}, \check{\alpha}_{H,b}, \check{\alpha}_{F,a}]$, need to satisfy equation (23). In this process, we need to take into consideration that these components vary with portfolio returns defined as
\[
\xi_t = \check{\alpha}' \hat{R}_{x,t}, \tag{25}
\]
where $\check{\alpha}$ is the asset holdings adjusted for a country’s steady-state income $\check{\alpha} = \frac{\check{\alpha}}{\beta Y}$. Moreover, excess asset returns $R_{x,t}$ and portfolio returns $\xi_t$ are interdependent. To overcome this simultaneity problem, Devereux and Sutherland (2011) suggest a two-step procedure: In the first step, the two components in equation (23) are expressed as functions of $\epsilon_t$ and $\xi_t$. In the second step, $\xi_t$ is expressed as a function of $\epsilon_t$ so that the behavior of consumption differential and excess returns can be expressed in terms of $\epsilon_t$ only.
Borrowing the notations from Devereux and Sutherland (2011) with minor modifications, I set up the system of equations in the first step as

\[
\hat{C}_{H,t+1} + \frac{\hat{P}_{H,t+1}}{\sigma} = D_{H1}\xi_{t+1} + D_{H2}\epsilon_{t+1} + D_{H3}z_{t+1} + O(\epsilon^2),
\]

(26)

\[
\hat{C}_{F,t+1} + \frac{\hat{P}_{F,t+1}}{\sigma} = D_{F1}\xi_{t+1} + D_{F2}\epsilon_{t+1} + D_{F3}z_{t+1} + O(\epsilon^2),
\]

(27)

\[
\hat{R}_{x,t+1} = R_{1}\xi_{t+1} + R_{2}\epsilon_{t+1} + O(\epsilon^2),
\]

(28)

where \(R_1, R_2, D_{i1}, D_{i2}, D_{i3}, i \in \{H, F\}\) are the coefficient matrices extracted from the first-order conditions of the model. \(R_1\) and \(D_{i1}\) capture the response of the two components (consumption differential and excess asset returns) to excess portfolio returns; \(R_2\) and \(D_{i2}\) capture their response to productivity shocks; and \(D_{i3}\) are their response to other state variables in the model summarized by \(z\). Next I impose the condition that \(\xi_{t+1}\) is related to excess returns via \(\xi_{t+1} = \tilde{\alpha}'\hat{R}_{x,t+1}\). Using this and equation (28) allows me to express \(\xi_{t+1}\) and \(\hat{R}_{x,t+1}\) in terms of \(\epsilon_{t+1}\):

\[
\xi_{t+1} = \tilde{H}\epsilon_{t+1}, \quad \text{where} \quad \tilde{H} = \frac{\tilde{\alpha}'R_2}{1 - \tilde{\alpha}'R_1};
\]

(29)

\[
\hat{R}_{x,t+1} = \tilde{R}\epsilon_{t+1} + O(\epsilon^2), \quad \text{where} \quad \tilde{R} = R_1\tilde{H} + R_2.
\]

(30)

Moreover, substituting for \(\xi_{t+1}\) in equations (26) and (27) using (29) gives

\[
\begin{cases}
\hat{C}_{H,t+1} + \frac{\hat{P}_{H,t+1}}{\sigma} = \tilde{D}_H\epsilon_{t+1} + D_{H3}z_{t+1} + O(\epsilon^2), & \text{where} \quad \tilde{D}_H = D_{H1}\tilde{H} + D_{H2}, \\
\hat{C}_{F,t+1} + \frac{\hat{P}_{F,t+1}}{\sigma} = \tilde{D}_F\epsilon_{t+1} + D_{F3}z_{t+1} + O(\epsilon^2), & \text{where} \quad \tilde{D}_F = D_{F1}\tilde{H} + D_{F2}.
\end{cases}
\]

(31)

Now that we have examined the two components separately as functions of innovations \(\epsilon_{t+1}\), we can multiply them to evaluate the portfolio determination condition (equation 23). In this process, elements representing information frictions will be loaded on the diagonal of the variance-covariance matrix of sectoral productivity shocks \(\Sigma\). Let \(f_s\) be the information frictions in sector \(s\), then the perceived variance-covariance matrices

\[\text{I assume } f_s \text{ is an additive friction for expositional purposes here. Alternatively, it can be modeled as a multiplier for the variance of foreign shocks (denoted as } f_{s1} \text{ in the text earlier). Qualitative predictions remain the same under two modeling assumptions.}\]
from country $H$’s and $F$’s perspective are respectively given by

$$
\Sigma_H = \Sigma + \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & f_a & 0 \\
0 & 0 & 0 & f_b
\end{bmatrix}, \quad \Sigma_F = \Sigma + \begin{bmatrix}
f_a & 0 & 0 & 0 \\
0 & f_b & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
$$

(32)

Since the ordering of asset returns follows $R_{H,a}, R_{H,b}, R_{F,a}, R_{F,b}$, households in country $H$ ($F$) incur information frictions for the 3rd and 4th (1st and 2nd) assets, which correspond to the lower right (upper left) corner the variance-covariance matrix.

With all the ingredients put together, the portfolio determination condition (equation 23) can be re-written as

$$
E_t[(\hat{C}_{H,t+1} - \hat{C}_{F,t+1} + \frac{\hat{\epsilon}_{t+1}}{\sigma})R_{x,t+1}] = \bar{R}\Sigma_H \bar{D}_H - \bar{R}\Sigma_F \bar{D}_F = \frac{T}{\sigma} + O(\epsilon^3).
$$

(33)

Different from the case in Devereux and Sutherland (2011), a closed-form solution to the portfolio choice problem cannot be derived in this framework. Instead, I use equation 33 to obtain the numerical solution to households’ asset holdings under various frictions.

The baseline numerical results are solved under the parametric assumptions summarized in table 4. I adopt the following standard assumptions from macroeconomics literature: (i) the annual discount factor is .95, and (ii) the coefficient of risk aversion is 2. In terms of consumption preference, I assume the elasticity of substitution between tradable sectors is 2 following Levchenko and Zhang (2016). Within a sector, economists including Baier and Bergstrand (2001) and Imbs and Mejean (2015) estimate the elasticity to be much greater according to sectoral trade data. Based on their estimates, I set the elasticity of substitution within a sector to be 5. Moreover, households are assumed to spend more on domestic goods ($\mu > 0.5$) and on comparative advantage sectors ($\psi_H > 0.5$). These assumptions skew aggregate price levels toward the prices of domestic comparative advantage sectors. Alternatively, one can introduce trade costs in the goods market instead of consumption home bias to generate the same comovement.

The other parameters, including the amount of endowments and the specification of productivity processes, are set arbitrarily since they will not change the qualitative prediction of this illustrative model. In the quantitative exercise, these parameters will be calibrated to match the data.
Table 4: Baseline Parametrization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Discount factor</td>
<td>0.95</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Coefficient of relative risk aversion</td>
<td>2</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Elasticity of substitution between sectors</td>
<td>2</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Elasticity of substitution within sectors</td>
<td>5</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Weight of domestic goods in within a sector</td>
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</tr>
<tr>
<td>$\psi_H$</td>
<td>Expenditure shares on comparative advantage sectors</td>
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</tr>
<tr>
<td>$\alpha$</td>
<td>Capital share in production</td>
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<tr>
<td>$\bar{L}$</td>
<td>Labor endowment</td>
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<td>$\bar{K}$</td>
<td>Capital endowment</td>
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<td>$\rho$</td>
<td>Autoregressive coefficient of productivity</td>
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</tr>
<tr>
<td>$\sigma_\epsilon$</td>
<td>Std. dev. of productivity shocks</td>
<td>0.25</td>
</tr>
</tbody>
</table>

3.2.2 Results from Comparative Statics Analysis

In this part, I examine the variation in sectoral home bias driven by sectoral productivity differences, transaction costs, and information frictions. Specifically, I graphically analyze the comparative statics that illustrate the impact of these factors on the portfolio choice of country $H$’s households.

In order to isolate the influence of comparative advantage on sectoral home bias, I first assume there is no transaction cost or information friction when depicting the change of domestic asset holdings with sectoral productivity differences in figure 2. Three findings are notable from the figure: First, households short-sell domestic assets in both sectors for risk hedging, reflected by the negative asset positions. To understand this, in this framework, both labor income risk and real exchange rate risk induce households to buy foreign assets in order to hedge risks, which is consistent with the arguments made by Baxter and Jermann (1997) and Coeurdacier (2009), among others.\footnote{The prediction can be different under alternative modeling assumptions. For example, Coeurdacier and Rey (2013) contend that parametric assumptions, in particular about the elasticity of substitution between goods and the share of goods in consumption bundles (e.g., whether there is consumption home bias), will determinate whether the real exchange rate risk causes home or foreign equity bias.}

Second, households hold fewer domestic assets of comparative advantage sectors as $\alpha_{H,a} < \alpha_{H,b}$. This is because the domestic comparative advantage sector (sector $a$ in country $H$, denoted as $Ha$ hereafter for brevity) exposes households to greater risks because its asset returns are more highly correlated with domestic labor income and decrease more closely with real exchange rate. Therefore, it is optimal for households in country $H$ to exhibit weaker sectoral home bias for sector $a$ than $b$. Third, the disparity between sectoral home
bias rises when $T$, the sectoral productivity difference, which also measures comparative advantage, increases. To understand this, the greater the value of $T$, the more risks are associated with the comparative advantage sector $Ha$. Therefore, households gradually switch from $Ha$ to $Hb$ assets, which are less risky. This explains the growing gap between the two asset positions when $T$ rises in figure 2.

Another interesting finding is that when $T$ increases, households not only raise their holdings of $Hb$ assets for intra-national risk hedging but also raise their holdings of foreign assets for inter-national risk hedging. As figure 3 suggests, aggregate domestic holdings $\alpha_H = \alpha_{Ha} + \alpha_{Fa}$ decrease with $T$. Hu (2020) analyzes the economic intuition behind this finding: Although the comparative disadvantage sector ($Hb$) can partially offset the real exchange rate risk, the degree of this intra-national risk hedging is rather limited in countries with high degrees of industrial specialization (captured by a higher value of $T$). Therefore, households from these countries need to tilt their portfolios more towards foreign assets for inter-national risk hedging.

I now proceed to analyze the impact of asset transaction costs on sectoral home bias. Since the effect of sectoral productivity difference on portfolio choice is analyzed earlier, I will fix the value of $T$ as 3 from now on. As figure 4 suggests, both asset curves are upward sloping, which indicates that households increase their holdings of domestic assets in both sectors when asset transaction costs $\tau$ rise. This result could be explained by the fact that transaction costs reduce the appeal of foreign assets as risk-hedging instruments, which prompts households to increase the weight of domestic assets in their
portfolios. Between the two domestic assets, the holdings of $Ha$ assets are more sensitive to the changes in the transaction cost $\tau$, as the slope of its curve is greater in figure 4. This is because in the case with no transaction costs, sector $Fa$ offers more risk-hedging benefits than $Fb$ for households in country $H$. To understand this, recall sector $Fb$ is country $F$’s comparative advantage sector. Hence country $H$ imports more in that sector, which increases the comovement of the returns to that sector with $H$’s macro fundamentals. Therefore, $Fb$ assets are not as good hedging instruments as $Fa$ assets from country $H$’s perspective. Nevertheless, the hedging benefits of $Fa$ assets diminish under the transaction costs which lower the returns to foreign investment. The costs lead $H$’s households to substitute $Ha$ for $Fa$ assets in their portfolios, which explains the catch-up of sector $a$’s home bias, as is shown in figure 4.

Last but not least, I examine sectoral home bias under information frictions. Transactions costs are set as a constant (1e-4) and sectoral information frictions are assumed to be the same ($f_a = f_b = f$). Figure 5 presents the results of sectoral home bias, which share several similarities with figure 4. First, households raise their holdings of domestic assets in the presence of information frictions. Second, the increase in domestic holdings is more pronounced for the comparative advantage sector $Ha$. These similarities imply that much of the analysis on transaction costs can also be applied here to information frictions: If households perceive foreign assets as riskier under information asymmetry, they will replace foreign assets — especially in comparative advantage sectors — with domestic assets, even though foreign assets provide more hedging benefits. As figure 5
Figure 4: Sectoral Home Bias and Transaction Costs

suggests, if information frictions are large enough, they will dominate the risk-hedging channel by tilting portfolios towards the domestic comparative advantage sector such that $\alpha_{H,a} > \alpha_{H,b}$. Therefore, households exhibit stronger home bias in comparative advantage sectors, even if there is no difference in sectoral information frictions.

As is discussed earlier, information asymmetry between domestic and foreign assets can be exacerbated in comparative advantage sectors because households are less likely to acquire knowledge about foreign assets in the sectors where their country is competitive. To explore this possibility, I show sectoral home bias under heterogenous information frictions. In particular, I assume the information friction in sector $a$ is twice that in sector $b$ ($f_a = 2f_b = 2f$). Figure 6 illustrates the result, which suggests that the greater information frictions in sector $a$ raise $H$’s holdings of $Ha$ assets even further when the households perceive $Fa$ assets as riskier. Therefore, the gap between sectoral home bias widens under heterogenous information frictions across sectors. This finding confirms my hypothesis that households may favor domestic assets in comparative advantage sectors to a greater extent when information asymmetry worsens in those sectors.

To conclude the theory section, households hold fewer domestic assets in comparative advantage sectors for risk hedging. However, if market frictions in the form of transaction costs and information asymmetry are sufficiently large, households will exhibit a stronger home bias in comparative advantage sectors. The empirical findings in the previous section suggest that market frictions potentially dominate risk-hedging motives in driving the variation of sectoral home bias. Nevertheless, the empirical analysis cannot quantify
the magnitude of the frictions as well as the contribution of each friction to home bias. Therefore, I will conduct a quantitative assessment using a calibrated model to disentangle the effects of various frictions.

4 Quantitative Assessment

In this section, I conduct numerical analysis with a calibrated model to quantify the frictions and explore their effects on sectoral home bias. First, I extend the symmetric two-country two-sector framework built in the theory section to a model with a large group of countries and sectors. After that, I calibrate the model to fit international trade and financial data. Finally, I run a set of counterfactual exercises to disentangle the effects of frictions.

4.1 Extended Model

The setup of the extended model is modified from Hu (2020) where I examine the influence of industrial specialization on country-level home bias. I modify that model by adding financial frictions so as to match both the real side and the financial side of the economy. In the extended quantitative model, I employ the trade framework developed by Eaton and Kortum (2002) (EK hereafter). The main benefits of using the trade framework are twofold. First, the EK model introduces intra-sectoral trade with minimal parameter restrictions on households’ consumption preference. More importantly, sectoral productivity which shapes comparative advantage can be calibrated with the trade data based on the EK model. Following an extensive literature that uses the model to
examine the macro implications of trade patterns such as Levchenko and Zhang (2016), Caliendo and Parro (2015), and Uy et al. (2013), I extend the original EK model by incorporating both tradable and nontradable sectors.

There are $I$ countries and $S+1$ industries in the extended model. The consumption of a representative household in country $i \in \{1, 2, ..., I\}$ is a Cobb-Douglas composite of $S$ tradable sectors and one nontradable sector denoted as $N$:

$$C_{i,t} = C_{i,T,t}^{\mu_i} C_{i,N,t}^{1-\mu_i} = \left( \sum_{s=1}^{S} \psi_s C_{i,s,t}^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} C_{i,N,t}^{\frac{1-\mu_i}{\phi-1}};$$  \hspace{1cm} (34)

where $\mu_i$ stands for the weight of the tradable bundle $C_{i,T}$ in country $i$’s consumption. The Cobb-Douglas specification implies that the elasticity of substitution between tradable and nontradable sectors is 1, which falls within the normal range estimated in the macro literature (see Ostry and Reinhart (1992) and Tesar and Werner (1995) among others). Consumption of the tradable bundle is a CES composite of consumption in different tradable sectors $s \in \{1, 2, ..., S\}$. $\psi_s$ denotes the expenditure share on sector $s$ and $\phi$ denotes the elasticity of substitution between sectors within the tradable bundle.

Following the EK model, I assume there is a continuum of varieties $z \in [0, 1]$ in each sector. Households’ consumption of sector $s$ is a CES aggregate of different varieties with elasticity of substitution $\epsilon$:

$$C_{i,s,t} = \left[ \int_0^1 C_{i,s,t}(z)^{\frac{1}{\epsilon-1}} dz \right]^{\frac{1}{\epsilon-1}}. \hspace{1cm} (35)$$

A variety can be produced either at home or abroad and then traded across borders. At time $t$, country $i$ can produce variety $z$ in sector $s$ with efficiency $A_{i,s,t}(z)$, which is drawn from the Fréchet distribution:

$$F_{i,s,t}(A) = \exp(-T_{i,s,t} A^{-\theta}). \hspace{1cm} (36)$$

$T_{i,s,t}$ captures the central tendency of sectoral productivity: the higher the $T_{i,s,t}$, the more productive country $i$ is in sector $s$ at time $t$. Moreover, I add dynamics to the EK model by assuming that $T_{i,s,t}$ follows an AR(1) process subject to shocks around its steady
state:

\[ T_{i,s,t} = \rho T_{i,s,t-1} + (1 - \rho)\bar{T}_{i,s} + \varepsilon_{i,s,t}. \]  

(37)

For the tradable sectors, country \( i \) incurs iceberg trade costs \( t_{i,t} \) when exporting to the rest of the world. As is argued by Coeurdacier (2009), trade costs affect not only commodity flows but also financial flows across countries. Therefore, it is important to include them in the quantitative model. Given the trade costs, the price of variety \( z \) in sector \( s \) exported from country \( i \) to the rest of the world becomes

\[ p_{i,s,t}(z) = \frac{t_{i,t}c_{i,s,t}}{A_{i,s,t}(z)}, \]  

(38)

where production cost \( c_{i,s,t} \) combines wage \( w_{i,t} \) and capital rental fee \( r_{i,t} \) with sectoral capital intensity \( \alpha_s \)

\[ c_{i,s,t} = r_{i,t}^{\alpha_s} w_{i,t}^{1-\alpha_s}. \]  

(39)

As in the baseline model, labor and capital are endowments that are mobile across sectors but immobile across countries. Factor prices \( r_{i,t} \) and \( w_{i,t} \) are pinned down by the market-clearing conditions:

\[ \sum_{k \in \{1, 2, \ldots, S, N\}} L_{i,k,t} = L_{i,t}, \quad \sum_{k \in \{1, 2, \ldots, S, N\}} K_{i,k,t} = K_{i,t}. \]  

(40)

Under the assumption of balanced trade, the aggregate consumption expenditure in country \( i \) equals the sum of endowment income:

\[ X_{i,t} = w_{i,t}L_{i,t} + r_{i,t}K_{i,t}. \]  

(41)

Aggregating the varieties in equation 38 gives sectoral price levels and trade flows based on the EK model (see Appendix B.1 for detailed derivation).

In the equity market, there are \( I \times (S + 1) \) types of stocks, each representing sector \( k \in \{1, 2, \ldots, S, N\} \) from country \( i \in \{1, 2, \ldots, I\} \). Dividends of the assets, defined as the claims to capital income as in the theory section, will be proportional to the sectoral

---

12 This is similar to the specification of productivity shocks in a standard DSGE model. To get the numerical solution to steady-state portfolios, I need to analyze the first-order dynamics of the economy around a deterministic steady state. The AR(1) specification makes this analysis tractable. \( \bar{T}_{i,s} \) will be calculated as the average of \( T_{i,s,t} \) over the sample period.

13 The balanced-trade assumption isolates the implications of risk-hedging for foreign investment which could also be driven by global trade imbalances. I relax the assumption in Appendix C.2 and confirm the robustness of the quantitative results.
income earned in domestic and foreign markets denoted as \( Y_{i,k,t} \)

\[
d_{i,k,t} = \alpha_k Y_{i,k,t}.
\] (42)

Ideally, a household in country \( i \) should construct a portfolio consisting of all these available stocks. However, solving the portfolio choice problem with such a large number of countries and sectors is computationally challenging.\(^{14}\) For this reason, when I analyze country \( i \)'s home bias, I do not distinguish specific destinations of foreign investment but group the rest of the world as a whole, so households in country \( i \) choose among \( 2 \times (S + 1) \) assets. In other words, the model collapses to a two-country framework from each country’s perspective: country \( i \) sees itself as home and the rest of the world as foreign (whose variables are asterisked). Given this two-country specification, households in country \( i \) construct the optimal portfolio to maximize their expected lifetime utility subject to the budget constraint

\[
X_{i,t} + \sum_{k \in \{1,2,\ldots,S,N\}} \left[ q_{i,k,t}(\nu_{i,k,t+1} - \nu_{i,k,t}) + q_{i,k,t}^*(\nu_{i,k,t+1}^* - \nu_{i,k,t}^*) \right] = w_{i,t}L_{i,t} + \sum_{k \in \{1,2,\ldots,S,N\}} \left( d_{i,k,t} \nu_{i,k,t} + d_{i,k,t}^* \nu_{i,k,t}^* \right).
\] (43)

\( X_{i,t} \) is the total consumption expenditure in country \( i \). \( \nu_{i,k,t} \) (\( \nu_{i,k,t}^* \)) denotes the number of domestic (foreign) shares country \( i \) holds of sector \( k \) at time \( t \). \( q_{i,k,t} \) (\( q_{i,k,t}^* \)) represents domestic (foreign) asset prices. Together with domestic (foreign) dividends \( d_{i,k,t} \) (\( d_{i,k,t}^* \)), they define the sectoral financial return

\[
R_{i,k,t} = \frac{q_{i,k,t} + d_{i,k,t}}{q_{i,k,t-1}}, \quad R_{i,k,t}^* = \frac{q_{i,k,t}^* + d_{i,k,t}^*}{q_{i,k,t-1}^*}.
\] (44)

I introduce two financial frictions in the form of transaction costs and information asymmetry. As in the theory section, asset transaction costs are modeled as a tax on foreign returns, and information frictions are modeled as higher perceived variance of foreign assets. Both frictions are second-order in magnitude (i.e. proportional to the variance of innovations). \( \tau_i \) denotes the transaction costs country \( i \) incurs when investing in foreign assets and the transaction costs the rest of the world incurs when investing in

\(^{14}\)Given the sparsity of bilateral trade data at the sector level, the large matrix that covers the bilateral ties for all the countries and sectors is badly scaled. Using this matrix to derive countries’ portfolio choice with the perturbation method yields inaccurate results.
country $i$’s assets; it appears in the Euler equations at home and abroad:

$$
E_t \left[ \frac{U'(C_{i,t+1})}{P_{i,t+1}} R_{i,s,t+1} \right] = E_t \left[ \frac{U'(C_{i,t+1})}{P_{i,t+1}} (1 - \tau_i) R^*_{i,k,t+1} \right],
$$

$$
E_t \left[ \frac{U'(C^*_{i,t+1})}{P_{i,t+1}} R^*_{i,k,t+1} \right] = E_t \left[ \frac{U'(C^*_{i,t+1})}{P_{i,t+1}} (1 - \tau_i) R^*_{i,k,t+1} \right].
$$

(45)

When evaluating the second-order Taylor expansion of the Euler equations to derive portfolios following Devereux and Sutherland (2011)’s method, I consider sectoral information frictions $f_{i,k}$, which are added to the variance of foreign sectoral productivity shocks $\sigma^2_{i,k}$. Therefore, the perceived variance-covariance matrix of domestic and foreign sectoral productivity shocks from the country’s perspective is the sum of the matrix of the shocks $\Sigma_i$ and a diagonal matrix containing the information frictions

$$
\hat{\Sigma}_i = \Sigma_i + \begin{bmatrix}
0 & \ldots & \ldots & 0 \\
\vdots & \ddots & \vdots & \vdots \\
0 & f_{i,1} & 0 & \ldots \\
\vdots & \ddots & \ddots & \vdots \\
0 & \ldots & f_{i,S} & 0 \\
\end{bmatrix}.
$$

(46)

where the ordering of sectoral asset returns is $R_{i,1}, ..., R_{i,S}, R^*_{i,1}, ..., R^*_{i,S}$.

Using the same strategies as in the theory section, I derive the portfolio determination condition\textsuperscript{15}

$$
E_t [(\hat{C}_{i,t+1} - \hat{C}^*_{i,t+1} + \frac{\hat{e}_{i,t+1}}{\sigma}) \hat{R}_{xi,t+1}] = \bar{R}_i \hat{\Sigma}_i \bar{D}'_i - \bar{R}_i \Sigma_i \bar{D}^*_i = \frac{T_i}{\sigma} + O(\epsilon^3).
$$

(47)

Here $\hat{R}_{xi,t+1}$ and $T_i$ are the vectors of excess financial returns and transaction costs; $\bar{R}_i$ is the response of excess returns to sectoral productivity shocks; $\bar{D}_i$ ($\bar{D}^*_i$) captures how the inflation-adjusted domestic (foreign) consumption reacts to the shocks. I will use equation 47 to numerically solve for households’ asset positions under various frictions.

The calibration strategy for the real side of the economy is similar to that used in Hu (2020) and outlined in Appendix B.2. In particular, sector-level productivity and country-level trade costs in country $i$ are estimated to match (1) the country’s share of all the

\[\text{This is similar to equation 33 in the theory section. See Appendix B.1 for the detailed derivation in this extended model.}\]
countries’ exports in sector \( s \) and (2) the country’s overall export-to-output ratio. On the financial side of the economy, I calibrate information frictions and transaction costs to match the data for both sector- and country-level home bias of the countries whose financial data are available in the Factset/Lionshare database. The financial frictions are exactly identified since the number of targets equals the number of unknowns.\(^\footnote{For each country \( i \), the unknown parameters include 1) \( S + 1 \) information frictions (for \( S \) tradable and one nontradable sector) and 2) one country-level asset transaction cost. The targets include \( S + 1 \) sectoral home bias and one national home bias. Note when matching the nontradable sector’s home bias, I group the nontradable industries in table A.2 into one nontradable sector, whose sectoral home bias is the weighted average home bias for the country’s nontradable industries observed in the data.}\

In addition to this baseline model, I consider two extensions by incorporating 1) global trade imbalances and 2) intermediate inputs and input-output linkages. In particular, I re-calibrate and solve the model to 1) match the trade surplus/deficit data from the World Bank and 2) reflect sectoral input-output linkages based on the parametrization from Di Giovanni et al. (2014). Appendix C.2 reports the quantitative results, which are consistent with those in the baseline model.

Besides the model description presented in this section, Appendix B provides more details of the quantitative model: Section B.1 discusses the determination of endogenous variables and equilibrium conditions in the model. Section B.2 outlines the calibration and algorithm used to obtain numerical solutions.

4.2 Numerical Results

In this section, I first evaluate the financial frictions implied by the model. After that, I conduct a set of counterfactual analyses to quantify the effects of each friction on sectoral home bias.

For each country \( i \), its households face transaction costs \( \tau_i \) and sectoral information frictions \( f_{i,s} \) when investing abroad, whose values are estimated to match the country’s sectoral as well as national home bias. Table 5 presents the summary statistics of these financial frictions estimated from the calibrated model. Due to the perturbation method used to derive portfolios, a small change in the frictions can shift asset positions drastically. Therefore, the magnitude of the estimates is small. Moreover, I don’t impose restrictions on the sign or value of the frictions when conducting the estimation. A positive (negative) estimate implies that the friction under examination tilts portfolios towards home (foreign) assets.

As is reported in table 5, the estimated asset transaction costs have a mean of 8.2e-6
Table 5: Summary statistics of the estimated financial frictions

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\tau}_i$</td>
<td>8.2e-6</td>
<td>9.8e-5</td>
<td>-8.2e-5</td>
<td>6.1e-4</td>
</tr>
<tr>
<td>$\hat{f}_{i,s}$</td>
<td>1.3e-5</td>
<td>4.3e-4</td>
<td>-4.1e-3</td>
<td>6.3e-3</td>
</tr>
</tbody>
</table>

$\hat{\tau}_i$ is estimated country-level transaction costs modeled as taxes on foreign returns. $\hat{f}_{i,s}$ denotes estimated information frictions modeled as higher perceived variances for foreign sectoral productivity shocks.

and standard deviation of 9.8e-5. Table A.4 lists the costs by country, which shows that the value ranges from -8.2e-5 (Belgium) to 6.1e-4 (Russia) in the sample. Most OECD countries’ values are at the low end of the spectrum, while countries including Russia, China, South Africa, Malaysia, and Romania are among the countries whose transaction costs are the highest. When I explore the bivariate relationship between the estimated transaction costs with the Chinn-Ito index averaged over the sample period (denoted as $\bar{CI}$) using the regression:

$$\hat{\tau}_i = \alpha + \beta \bar{CI}_i + \epsilon_i,$$  (48)

I find that a 1 standard-deviation increase in transaction costs is associated with a 0.29 standard-deviation decrease in financial account openness measured by the Chinn-Ito index. The coefficient estimate $\beta$ is significantly negative at the 1 percent level. The negative correlation between the two variables illustrates that the model performs well in predicting that investors from countries with a higher degree of financial account openness face greater transaction barriers when holding foreign assets.

Table 5 also reports the sectoral information frictions estimated from the calibrated model. The mean value of the estimates in the sample is 1.3e-5 and the standard deviation is 4.3e-4. The estimates range from -4.1e-3 (representing the investment in the oil and coal industry of Ireland) to 6.3e-3 (the pharmaceutical industry of the U.A.E.). When comparing sectoral estimates averaged across countries (table A.4), I find oil and coal show the lowest information frictions, while the frictions in food, non-ferrous metals, and pharmaceuticals are among the highest. In the next step I test a hypothesis raised earlier: greater informational frictions exist in sectors where countries exhibit stronger comparative advantage. To test this hypothesis, I regress the estimated information frictions ($\hat{f}_{i,s}$) on revealed comparative advantage averaged over the sample period ($RC\bar{A}_{i,s}$) when controlling for country fixed effects ($\gamma_i$)

$$\hat{f}_{i,s} = \alpha + \beta RC\bar{A}_{i,s} + \gamma_i + \epsilon_{i,s}.$$  (49)

32
The coefficient estimates suggest that when RCA increases by 1%, information frictions increase by 4.4e-5 (or 0.09 standard deviations). The positive comovement is significant at the 10 percent level. This finding confirms the hypothesis that investors are subject to greater information frictions when holding foreign assets in the sectors where their countries reveal a comparative advantage. Therefore, information frictions can potentially explain the finding in the empirical section that sectoral home bias is stronger in comparative advantage sectors.

To further disentangle the contribution of financial frictions to sectoral home bias, I conduct a series of counterfactual analyses in which I set one friction to zero sequentially and examine how sectoral home bias responds. After computing the counterfactual portfolio, I regress the change in sectoral home bias relative to the data (denoted as $\Delta HB_{i,s}$) on the financial friction that is excluded:

$$\Delta HB_{i,s,\tau} = \alpha + \beta \hat{\tau}_{i} + \gamma_{i,\tau} + \epsilon_{i,s,\tau},$$

$$\Delta HB_{i,s,f} = \alpha + \beta \hat{f}_{i,s} + \gamma_{i,f} + \epsilon_{i,s,f}.$$

The estimated coefficient for $\beta_{\tau}$ suggests that the elimination of a 1 standard-deviation asset transaction costs lowers sectoral home bias by 0.33 standard deviations. The estimated coefficient for $\beta_{f}$ suggests that the elimination of a 1 standard-deviation information frictions lowers sectoral home bias by 0.02 standard deviations. Both results are significant at the 1 percent level. These findings suggest that the two financial frictions tilt investors’ portfolios toward domestic assets. Therefore, lifting the frictions raises the share of foreign assets in portfolios and reduces home bias.

Table 6 presents the median sectoral home bias across countries and sectors predicted by the quantitative model under various circumstances. Column (1) reports the original home bias calibrated to the data under both asset transaction costs and information frictions. The median sectoral home bias observed in the sample is 0.291. In column (2) where I set asset transaction costs ($\hat{\tau}_{i}$) to zero, the resulting median sectoral home bias decreases to 0.096. Based on these values, asset transaction costs account for $\frac{0.291 - 0.096}{0.291} = 67\%$ sectoral home bias. Similarly, in column (3) where I shut down information frictions, sectoral home bias is reduced to 0.260. Therefore, $\frac{0.291 - 0.260}{0.291} = 10.7\%$ sectoral home bias can potentially be explained by information asymmetry. From this perspective, asset transaction costs are nearly as six times important as information frictions in explaining investors’ portfolio choice at the sector level.

Table 6 also reports the median national home bias across countries predicted by
Table 6: Predicted home bias in counterfactual analysis

<table>
<thead>
<tr>
<th></th>
<th>Original home bias</th>
<th>No transaction costs</th>
<th>No informational frictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$HB_{i,s}$</td>
<td>0.291</td>
<td>0.096</td>
<td>0.260</td>
</tr>
<tr>
<td>$HB_i$</td>
<td>0.460</td>
<td>0.418</td>
<td>0.419</td>
</tr>
</tbody>
</table>

This table reports the median sectoral home bias across countries and sectors $HB_{i,s}$ and median national home bias $HB_i$ across countries predicted by the quantitative model. Column (1) reports the original home bias calibrated to match the data. Column (2)-(3) report the home bias in counterfactual analysis when financial frictions are set to zero.

The quantitative model. In columns (2) and (3) where I turn off the two frictions, the resulting national home bias drops from 0.460 to 0.418 and 0.419, respectively. This finding suggests that the two frictions each explain about 9% national home bias. The fact that the change in column (2) is slightly larger than that in column (3) implies that asset transaction costs play a more important role in prohibiting international diversification at the country level, consistent with the finding at the sector level.

It is also worth noting that the change in national home bias is significantly smaller than that in sectoral home bias when frictions are shut down. This indicates that additional factors contribute to home bias at a greater scale. One potential explanation can be the stronger home bias investors exhibit in the nontradable sector, documented in empirical section. If investors’ risk-hedging motives mainly drives this stronger home bias, eliminating financial frictions will not significantly change investors’ asset positions. I confirm this hypothesis by finding from the numerical results that home bias in the nontradable sector barely changes in the scenario where there is no financial friction. This finding corroborates the theory proposed in the international finance literature including Stockman and Dellas (1989), Obstfeld and Rogoff (2001), and Collard et al. (2007) that investors may skew their portfolio towards domestic assets, especially domestic nontradable sectors’ assets to hedge against the fluctuation in real exchange rates. Assets of nontradable sectors account for 51% of investors’ portfolios averaged across countries in the sample. Given this great weight, risk-hedging motives remain to be a major explanation for national home bias.
5 Conclusion

This paper contributes to the literature on the well-known home bias puzzle in international finance by adding a sectoral dimension. First, I compile the sector-level home bias of a large group of countries and sectors using unique financial datasets. This novel index provides unprecedentedly detailed information for studying the pattern and determinants of home bias. Second, I develop an illustrative two-country two-sector model to explain the impact of multiple frictions on equity home bias. This theoretical model, different from most existing papers on the topic that abstract from sectoral heterogeneity, extends and deepens our understanding of investors’ portfolio choices. Lastly, I take the theory to the data by conducting a quantitative assessment of a calibrated multi-sector DSGE model. The numerical exercise disentangles the contribution of various frictions to the home bias puzzle.

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 for risk-hedging purposes at the country level, but there is little research at the sector level with corporate instead of government debt. Second, examining micro-level asset positions will allow us to further exploit the variation across holders and assets to better understand the puzzle. For example, Maggiori et al. (2020) assemble the security-level bond positions of worldwide mutual funds and find much of the home bias can be attributed to currencies of denomination of debt. Third, this paper focuses on the effect of industrial structure on portfolio choice, while it is also meaningful to examine the impact of asset allocations on the real side of the economy. When there exist financial constraints such as those introduced by Manova (2013), sectors less subject to market frictions are better positioned to accumulate growth. Therefore, the pattern of home bias has a feedback effect on countries’ long-run industrial structure. Current data are not sufficient to conduct the analysis yet since studying this channel requires long-term portfolio data given that industrial restructuring is a gradual and prolonged process, so I defer it to future research. By including these extensions, such papers will provide us with a better understanding of the determinants and impacts of international capital flows.
References


Kollmann, R. International portfolio equilibrium and the current account. 2006.


Appendices

A Tables and Figures

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: Comparison of Home Bias Constructed with Factset/Lionshare and IFS Data

Note: This figure plots the country-level home bias constructed with the Factset/Lionshare data against Coeurdacier and Rey (2013)’s constructed with the IMF’s IFS data (both as of 2008). The two indices are consistent since most of the points lie on or close to the 45-degree line.
Figure A.3: 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.4: U.K. Home Bias by Sector

Note: This chart is a histogram of the U.K. sectoral home bias index averaged over time. The formula used to construct the index is $HB_{i,s} = 1 - \frac{\text{Share of Sector } s \text{ Foreign Equities in Country } i \text{ Equity Holdings}}{\text{Share of sector } s \text{ Foreign Equities the World Market Portfolio}}$. The data used to construct this index are from Factset/Lionshare and Datastream.
Table A.1: Correspondence between Factset and Datastream Industries

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<th>Description</th>
<th>ICB</th>
<th>Description</th>
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</tr>
<tr>
<td>2415</td>
<td>Foods: Specialty/Candy; Foods: Meat/Fish/Dairy</td>
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<td></td>
</tr>
<tr>
<td>2420 2425</td>
<td>Beverages: Non-Alcoholic; Beverages: Alcoholic</td>
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<td>Beverages</td>
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<td>2430</td>
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<td>TOBAC</td>
<td>Tobacco</td>
</tr>
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<td>CLTHG</td>
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<tr>
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<td>Forest Products</td>
<td>FORST</td>
<td>Forestry</td>
</tr>
<tr>
<td>2230</td>
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<td>FSTPA</td>
<td>Paper</td>
</tr>
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</tr>
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Note: ICB stands for Dow Jones/FTSE’s Industry Classification Benchmark, which is adopted by Datas-}
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Note: This table lists the name and code of countries and sectors in the sample.
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Note: The sector code is based on the industries that appear in the financial datasets (see A.2). ISIC Rev.4. stands for International Standard Industrial Classification of All Economic Activities, Rev.4. I list all the ISIC sectors that correspond to the industries in the financial datasets.
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Note: This table lists the estimated financial frictions in the quantitative analysis by country and sector. $\tilde{\tau}_i$ denotes country-level asset transaction costs, and $\bar{f}_{i,s}$ denotes sectoral information frictions averaged across countries in the sample. See table A.2 for the code of sectors.
B Details on the Quantitative Model

In this part, I provide more details of the quantitative model: Section B.1 outlines how the equilibrium values of the endogenous variables are obtained in the model. Section B.2 discusses the calibration strategies and algorithm used to obtain numerical solutions to the model.

B.1 Model

I first describe the real side of the model. In this part, since the trade framework is relatively ‘static’ by nature, I omit the time subscript of the variables for brevity. A nice feature of the EK model is that prices and quantities in the goods market are endogenously determined by productivity and trade costs analytically. Given the price in equation 38, the share of country $i$’s exports in the world market for sector $s$ equals the probability that the price of $i$’s goods is the lowest:

$$
\pi_{i,s} = \frac{T_{i,s}(t_{i,C_{i,s}})^{-\theta}}{\Phi_{s}}
$$

where

$$
\Phi_{s} = \sum_{i} T_{i,s}(t_{i,C_{i,s}})^{-\theta}.
$$

(B.1)

Meanwhile, the consumption price of sector $s$ in country $i$ is given by

$$
P_{i,s} = \left[\Gamma\left(\frac{\theta + 1 - \epsilon}{\theta}\right)\right]^{1/\theta} \frac{1}{\Phi_{i,s}}^{1/\theta} \Phi_{s}^{1/\theta} - 1
$$

where

$$
\Phi_{i,s} = \Phi_{s} - T_{i,s}(t_{i,C_{i,s}})^{-\theta}.
$$

(B.2)

The price of the nontradable sector $P_{i,N}$ is obtained in a similar way when trade costs are assumed to be sufficiently large

$$
P_{i,N} = \Gamma\left(\frac{\theta + 1 - \epsilon}{\theta}\right)T_{i,N}^{-\frac{1}{\theta}} - 1
$$

(B.3)

Let $X_{i}$ denote country $i$’s aggregate consumption expenditure, therefore its expenditure in the nontradable sector becomes

$$
X_{i,N} = (1 - \mu_{i})X_{i} = (1 - \mu_{i})(w_{i}L_{i} + r_{i}K_{i}).
$$

(B.4)

Similarly, sectoral expenditure in the tradable sectors are determined by consumers’ optimality conditions

$$
X_{i,s} = \mu_{i}\psi_{s}\left(\frac{P_{i,s}}{P_{i}}\right)^{1 - \phi} X_{i},
$$

(B.5)
where the price of the tradable bundle and aggregate price level in country $i$ are

$$P_{1,t}^{1-\phi} = \sum_{s=1}^{S} \psi_{s} P_{1,t}^{1-\phi}, \quad P_{1} = \mu_{i}^{1-\mu_{i}} (1 - \mu_{i})^{\mu_{i}-1} P_{1,t}^{1-\mu_{i}}. \quad (B.6)$$

Sectoral income $Y_{i,s}$ is therefore determined by the goods market clearing conditions:

$$Y_{i,s} = \frac{T_{i,s}(c_{i,s})^{-\theta}}{\phi_{i,s}} X_{i,s} + \pi_{i,s} \sum_{j \neq i}^{I} X_{j,s}, \quad Y_{i,N} = X_{i,N}. \quad (B.7)$$

Therefore, the country-level export-to-output ratio is given by

$$E2Y_{i} = \frac{\sum_{s=1}^{S} (\pi_{i,s} \sum_{j \neq i}^{I} X_{j,s})}{Y_{i,N} + \sum_{s=1}^{S} Y_{i,s}}. \quad (B.8)$$

Based on sectoral factor intensity, sectoral factor allocations should satisfy

$$L_{i,s} = (1 - \alpha_{s}) Y_{i,s} w_{i}, \quad K_{i,s} = \alpha_{s} \frac{Y_{i,s}}{r_{i}}, \quad (B.9)$$

$$L_{i,N} = (1 - \alpha_{N}) Y_{i,N} \frac{w_{i}}{r_{i}}, \quad K_{i,N} = \alpha_{N} \frac{Y_{i,N}}{r_{i}}, \quad (B.10)$$

which in the equilibrium should clear the factor markets:

$$\sum_{k \in \{1,2,\ldots,S,N\}} L_{i,k} = L_{i}, \quad \sum_{k \in \{1,2,\ldots,S,N\}} K_{i,k} = K_{i}. \quad (B.11)$$

Besides these ‘domestic’ variables of country $i$, ‘foreign’ variables (marked with asterisks below) that represent the rest of the world from $i$’s perspective also need to be determined. The foreign cost of production in sector $k \in \{1,2,\ldots,S,N\}$

$$c_{i,k}^{*} = r_{i}^{*} \alpha_{k} w_{i}^{1-\alpha_{k}} \quad (B.12)$$

is determined by foreign factor prices approximated as

$$r_{i}^{*} = \sum_{j \neq i}^{I} r_{j} K_{j}, \quad w_{i}^{*} = \frac{\sum_{j \neq i}^{I} w_{j} L_{j}}{\sum_{j \neq i}^{I} L_{j}}. \quad (B.13)$$

This approximation ensures that the total factor income added across countries matches the data.
Given the production cost, foreign sectoral productivity in a tradable sector $s$ is calibrated to match country $i$’s trade flows with the rest of the world solved earlier. Therefore, it is recovered from

$$\Phi_{i,s} = T_{i,s} c_{i,s}^{-\theta} + T_{i,s}^* c_{i,s}^{s-\theta}.$$  \hspace{1cm} (B.14)

This productivity $T_{i,s}^*$ is then used to calculate the foreign sectoral income

$$Y_{i,s}^* = c_{i,s}^{s-\theta} T_{i,s}^* \sum_j X_{j,s} \Phi_{j,s},$$  \hspace{1cm} (B.15)

which determines sectoral factor allocations

$$L_{i,s}^* = (1 - \alpha_s) \frac{Y_{i,s}^*}{w_{i}}, \quad K_{i,s}^* = \alpha_s \frac{Y_{i,s}^*}{r_{i}}.$$  \hspace{1cm} (B.16)

Moreover, sectoral productivity also helps to pin down the price at the sector level

$$P_{i,s}^* = \left[ \frac{\theta}{\theta + 1 - \epsilon} \left( T_{i,s} (t_{i,c_{i,s}})^{-\theta} + T_{i,s}^* c_{i,s}^{s-\theta} \right) \right]^{\frac{1}{1-\epsilon}},$$  \hspace{1cm} (B.17)

which in turn determines the price of the tradable bundle:

$$P_{i,T}^{1-\phi} = \sum_{s=1}^{S} \psi_s P_{i,s}^{1-\phi}.$$  \hspace{1cm} (B.18)

Similarly, the quantity of consumption in the tradable bundle is given by

$$C_{i,T}^{\phi-1} = \sum_{s=1}^{S} \frac{1}{\psi_s} \left( C_{i,s}^* \right)^{\phi-1} = \sum_{s=1}^{S} \frac{1}{\psi_s} \left( \sum_j^{I} \frac{X_{j,s}}{P_{i,s}^*} \right)^{\phi-1}.$$  \hspace{1cm} (B.19)

Next I assume the foreign consumption weight on tradables is calculated with the total consumption from all the other countries

$$\mu_i^* = \frac{\sum_{j \neq i} (\mu_j X_j)}{\sum_{j \neq i} X_j}.$$  \hspace{1cm} (B.20)

This assumption ensures that the world share of expenditure on tradable sectors matches
the data. Under this assumption, the aggregate foreign expenditure is given by

$$X_i^* = \frac{1}{\mu_i^*} P_{i,T}^* C_{i,T}^*,$$  \hspace{1cm} (B.21)

which yields the foreign expenditure on nontradables:

$$X_{i,N}^* = (1 - \mu_i^*) X_i^*.$$  \hspace{1cm} (B.22)

This in turn pins down the foreign factor employments in the production of the nontradable sector

$$L_{i,N}^* = (1 - \alpha_N) \frac{X_{i,N}^*}{w_i^*}, \quad K_{i,N}^* = \alpha_N \frac{X_{i,N}^*}{r_i^*}.$$  \hspace{1cm} (B.23)

Based on the Cobb-Douglas production function, foreign productivity in the nontradable sector is

$$T_{i,N}^* = \alpha_N^{-\alpha_N} (1 - \alpha_N)^{\alpha_N - 1} \frac{X_{i,N}^*}{K_{i,N}^* L_{i,N}^{1 - \alpha_N}}.$$  \hspace{1cm} (B.24)

using which sectoral productivity can be solved based on the EK model

$$P_{i,N}^* = \Gamma \left( \frac{\theta + 1 - \epsilon}{\theta} \right) \frac{1}{T_{i,N}^{1 - \epsilon}} c_{i,N}^*.$$  \hspace{1cm} (B.25)

This price and the price of tradables jointly determine the foreign aggregate price level

$$P_i^* = \mu_i^* (1 - \mu_i^*)^{\epsilon - 1} P_{i,T}^* P_{i,N}^{1 - \epsilon}.$$  \hspace{1cm} (B.26)

Last but not least, the market clearing conditions determine the foreign factor endowments as

$$\sum_{k \in \{1,2,...,S,N\}} L_{i,k}^* = L_i^*, \quad \sum_{k \in \{1,2,...,S,N\}} K_{i,k}^* = K_i^*.$$  \hspace{1cm} (B.27)

So far, I have described how domestic and foreign variables on the real side of the economy are endogenously determined in the model. When I collapse the original multi-country to a two-country model, I impose mild assumptions to make sure that the foreign variables will be calibrated to keep country $i$’s trade flows with the world consistent with the data. Moreover, the world aggregate factor income and expenditure patterns will also match what we observe in the real world.

On the financial side of the economy, the solution strategy is similar to that in the theory section. Here I assume there are two countries from each country $i$’s perspective, ei-
Moreover, reference of the two equations in B.29 yields the portfolio determination equation whose coefficients as a function of asset positions \( \hat{\alpha}_i \). To solve for \( \hat{\alpha}_i \), I set up the system of

\[
\begin{align*}
R'_x_{i,t} &= \begin{bmatrix} \hat{\ddot{R}}_{i,1,t} - \hat{\ddot{R}}^*_{i,N,t}, \hat{\ddot{R}}_{i,2,t} - \hat{\ddot{R}}^*_{i,N,t}, \ldots, \hat{\ddot{R}}_{i,S,t} - \hat{\ddot{R}}^*_{i,N,t} \end{bmatrix}, \\
R''_x_{i,t} &= \begin{bmatrix} \hat{\dddot{R}}_{i,1,t} - \hat{\dddot{R}}^*_{i,N,t}, \hat{\dddot{R}}_{i,2,t} - \hat{\dddot{R}}^*_{i,N,t}, \ldots, \hat{\dddot{R}}_{i,S,t} - \hat{\dddot{R}}^*_{i,N,t} \end{bmatrix}.
\end{align*}
\]

They show up in the second-order approximation of the Euler equations (45):

\[
\begin{align*}
E_t[\hat{\ddot{R}}_{x,t+1} + \frac{1}{2} \hat{\ddot{R}}^2_{x,t+1} + \frac{1}{2} \tau - (\sigma \hat{\dot{C}}_{i,t+1} + \hat{\dot{P}}_{i,t+1}) \hat{\dddot{R}}_{x,t+1}] &= \mathcal{O}(\epsilon^3), \quad (B.28) \\
E_t[\hat{\dddot{R}}_{x,t+1} + \frac{1}{2} \hat{\ddot{R}}^2_{x,t+1} - \frac{1}{2} \tau - (\sigma \hat{\ddot{C}}^*_{i,t+1} + \hat{\ddot{P}}^*_{i,t+1}) \hat{\dddot{R}}_{x,t+1}] &= \mathcal{O}(\epsilon^3). \quad (B.29)
\end{align*}
\]

where \( \tau \) denotes the vector of transaction costs \( \tau = [\tau_1, \ldots, \tau_s, 0, \ldots, 0] \). Taking the difference of the two equations in B.29 yields the portfolio determination equation

\[
E_t[(\hat{\dot{C}}_{i,t+1} - \hat{\dddot{C}}^*_{i,t+1} + \frac{\hat{\dot{e}}_{t+1}}{\sigma}) \hat{\dddot{R}}_{x,t+1}] = \frac{\tau}{\sigma} + \mathcal{O}(\epsilon^3). \quad (B.30)
\]

On the left hand side are two components: 1) cross-country consumption differentials adjusted for exchange rates and 2) asset excess returns. To solve for the steady-state portfolio, these components need to be written in terms of innovations in the model

\[
\epsilon'_i = \begin{bmatrix} \epsilon_{i,1,t}, \ldots, \epsilon_{i,S,t}, \epsilon_{i,N,t}, \epsilon^*_{i,1,t}, \ldots, \epsilon^*_{i,S,t} \end{bmatrix}, \quad (B.31)
\]

whose coefficients as a function of asset positions \( \hat{\alpha}_i = [\hat{\alpha}_{i,1}, \ldots, \hat{\alpha}_{i,S}, \hat{\alpha}_{i,N}, \hat{\alpha}_{i,1}^*, \ldots, \hat{\alpha}_{i,S}^*] \) need to satisfy equation B.30. In this process, we need to take into consideration that these components vary with portfolio returns defined as

\[
\epsilon_{i,t} = \hat{\alpha}_i \hat{\dddot{R}}_{x,i,t}, \quad (B.32)
\]

where \( \hat{\alpha}_i \) are the asset holdings adjusted for country i’s steady-state output \( \hat{\alpha}_i = \frac{\hat{\alpha}_i}{\beta Y_i} \). Moreover, \( \hat{\dddot{R}}_{x,i,t} \) may depend on \( \hat{\alpha} \) through \( \hat{\epsilon}_{i,t} \). To solve for \( \hat{\alpha}_i \), I set up the system of
equations as

\[
\hat{C}_{i,t+1} + \frac{\hat{P}_{i,t+1}}{\sigma} = D_{i1}\xi_{i,t+1} + D_{i2}\epsilon_{i,t+1} + D_{i3}z_{i,t+1} + O(\epsilon^2), \quad \text{(B.33)}
\]

\[
\hat{C}^*_{i,t+1} + \frac{\hat{P}^*_{i,t+1}}{\sigma} = D^*_{i1}\xi_{i,t+1} + D^*_{i2}\epsilon_{i,t+1} + D^*_{i3}z_{i,t+1} + O(\epsilon^2), \quad \text{(B.34)}
\]

\[
\hat{R}_{xi,t+1} = R_{i1}\xi_{i,t+1} + R_{i2}\epsilon_{i,t+1}, \quad \text{(B.35)}
\]

where \(R_{i1}, R_{i2}, D_{i1}, D_{i2}, D_{i3}, D^*_{i1}, D^*_{i2}, D^*_{i3}\) are coefficient matrices extracted from the first-order conditions in the model. In the next step, I combine equation B.32 and B.35 to express \(\xi_{i,t+1}\) and \(\hat{R}_{xi,t+1}\) in terms of \(\epsilon_{i,t+1}\):

\[
\xi_{i,t+1} = \tilde{H}_i\epsilon_{i,t+1}, \quad \text{where} \quad \tilde{H}_i = \frac{\tilde{\alpha}'_i R_{i2}}{1 - \tilde{\alpha}'_i R_{i1}}, \quad \text{(B.36)}
\]

\[
\hat{R}_{xi,t+1} = \tilde{R}_i\epsilon_{i,t+1} + O(\epsilon^2), \quad \text{where} \quad \tilde{R}_i = R_{i1}\tilde{H}_i + R_{i2}. \quad \text{(B.37)}
\]

Moreover, substituting for \(\xi_{t+1}\) in equation B.33 and B.34 using B.36 gives

\[
\begin{cases}
\hat{C}_{i,t+1} + \frac{\hat{P}_{i,t+1}}{\sigma} = \tilde{D}_i\epsilon_{i,t+1} + D_{i3}z_{i,t+1} + O(\epsilon^2), \quad \text{where} \quad \tilde{D}_i = D_{i1}\tilde{H}_i + D_{i2}. \\
\hat{C}^*_{i,t+1} + \frac{\hat{P}^*_{i,t+1}}{\sigma} = \tilde{D}^*_i\epsilon_{i,t+1} + D^*_{i3}z_{i,t+1} + O(\epsilon^2), \quad \text{where} \quad \tilde{D}^*_i = D^*_{i1}\tilde{H}_i + D^*_{i2}. 
\end{cases} \quad \text{(B.38)}
\]

So far, I have followed the same strategy as in the theory section to evaluate the two components on the left hand side of equation B.30 in B.37 and B.38 separately. Information frictions will be loaded on the diagonal of \(\Sigma_i\), the variance-covariance matrix of domestic and foreign sectoral productivity shocks, when we calculate the product of the two components. Let \(f_{i,s}\) be the information frictions in sector \(s\) for country \(i\)'s foreign investment, then the perceived variance-covariance matrices from country \(i\)'s viewpoint is given by

\[
\Sigma_i = \Sigma_i + \begin{bmatrix}
0 & \cdots & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & 0 \\
0 & \cdots & \cdots & 0 \\
\end{bmatrix}
\begin{bmatrix}
f_{i,1} & 0 & \cdots & 0 \\
0 & f_{i,2} & \cdots & \vdots \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & f_{i,S} \\
\end{bmatrix}
\begin{bmatrix}
0 \\
\vdots \\
0 \\
0 \\
\end{bmatrix}
\] \quad \text{(B.39)}
Putting together all the ingredients for the evaluation of equation B.30, one can re-write the portfolio determination condition as

\[
E_t[(\hat{C}_{i,t+1} - \hat{C}^*_{i,t+1} + \frac{\hat{e}_{i,t+1}}{\sigma})\hat{R}_{xi,i,t+1}] = \hat{R}_i\hat{\Sigma}_i\hat{D}'_i - \hat{R}_i\Sigma_i\hat{D}'_i = \frac{T_i}{\sigma} + \mathcal{O}(\epsilon^3). \tag{B.40}
\]

### B.2 Computation

The quantitative exercise covers 15 ISIC tradable sectors (the same sectors as in the empirical section) from about 60 countries, which account for more than 90 percent of world trade volume, over the sample period 2001-2014 (the same time frame as in the empirical section for most countries in the sample). On the real side of the model, four categories of parameters need to be calibrated: (1) standard parameters taken from the macro/trade literature, (2) sector-specific factors including capital intensity and consumption weights, (3) country-specific factors including endowments, trade costs, expenditure shares on the nontradable sector, and (4) country-sector-specific productivity. On the financial side are two frictions, including country-specific asset transaction costs and country-sector-specific information frictions.

Table B.1 summarizes the values of these variables in the quantitative exercise. Most of the parameters on the real side of the economy are discussed in detail by Hu (2020). Many country- and sector-specific parameters are readily available in the literature or data. However, sector-level productivity and country-level trade costs need to be calibrated to match (1) the country’s share of all the countries’ exports in sector \( s \) and (2) the country’s overall export-to-output ratio. The calibrated sectoral productivity is also used to compute the variance-covariance matrix of productivity shocks, including within- and cross-country correlations across sectors. On the financial side of the economy, information frictions and transaction costs are calibrated to minimize the distance between the data and numerical results for both sector- and country-level home bias.

The following paragraphs outline the detailed computation procedure to numerically solve the model. Step 1-5 describe how the steady-state values of the real variables are determined. Step 6-8 discuss how the financial parameters are calibrated when solving for portfolios.

**Step 1. Calculate steady-state factor endowments, GDP, and exports**

Obtain the data of country-level factor endowments and GDP (whose dynamic values
## Table B.1: Parametrization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Annual discount factor</td>
<td>0.95</td>
<td>Macro literature</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Coefficient of relative risk aversion</td>
<td>2</td>
<td>Macro literature</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Elasticity of substitution between sectors</td>
<td>2</td>
<td>Levchenko and Zhang (2016)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Dispersion of productivity efficiency</td>
<td>8.28</td>
<td>Eaton and Kortum (2002)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Persistence of sectoral productivity</td>
<td>0.95</td>
<td>U.S. BLS</td>
</tr>
<tr>
<td>$\psi_s$</td>
<td>Consumption weights within tradables</td>
<td></td>
<td>U.S. BEA</td>
</tr>
<tr>
<td>$\alpha_s$</td>
<td>Sectoral capital intensity</td>
<td></td>
<td>U.S. I-O matrix</td>
</tr>
<tr>
<td>$\mu_i$</td>
<td>Country $i$’s expenditure shares on nontradables</td>
<td></td>
<td>STAN and a fitted regression</td>
</tr>
<tr>
<td>$L_{i,t}$</td>
<td>Labor endowment</td>
<td></td>
<td>Number of employees from PWT</td>
</tr>
<tr>
<td>$K_{i,t}$</td>
<td>Capital endowment</td>
<td></td>
<td>Capital stock from PWT</td>
</tr>
<tr>
<td>$t_i$</td>
<td>Trade costs</td>
<td></td>
<td>Calibrated to match observed trade flows</td>
</tr>
<tr>
<td>$T_{i,s}$</td>
<td>Sectoral productivity</td>
<td></td>
<td>Calibrated to match observed trade flows</td>
</tr>
<tr>
<td>$f_{i,s}$</td>
<td>Information frictions</td>
<td></td>
<td>Calibrated to match observed home bias</td>
</tr>
<tr>
<td>$\tau_i$</td>
<td>Asset transaction costs</td>
<td></td>
<td>Calibrated to match observed home bias</td>
</tr>
</tbody>
</table>

are both taken from the Penn World Table (PWT)), and of sector- and country- level exports (from UN Comtrade). The mean values over the sample period will be used as the steady-state values of these variables in the calibrated model.

**Step 2. Form initial guess for factor prices**

Use the information in step 1 and country-level capital share $\alpha_i$ available from PWT to guess factor prices under the Cobb-Douglas assumption:

$$r_i = \alpha_i \frac{Y_i}{K_{i,t}}, \quad w_i = (1 - \alpha_i) \frac{Y_i}{L_{i,t}} \tag{B.41}$$

**Step 3. Calibrate productivity and trade costs to match trade flows**

Use the factor prices in Step 2 and solve for sectoral productivity $T_{i,s}$ and trade cost $t_i$ to match (1) country $i$’s share of all the countries’ exports in sector $s$ ($\pi_{i,s}$), and (2) the country’s overall export-to-output ratio ($E2Y_i$). This involves plugging $w_i$, $r_i$, $T_{i,s}$ and $t_i$ in equation B.1 through B.8 until the two target variables match the data.

**Step 4. Update factor prices to clear the factor market**

Plug the estimated productivity and trade costs from Step 3, follow equation B.9 through B.11 to check whether the country-level factor endowments predicted by the model match those in the data. If not, repeat Steps 3 and 4 until the updated factor
prices satisfy the factor market clearing conditions.

**Step 5. Solve all the domestic and foreign real variables**

Given the equilibrium factor prices obtained in Step 4, repeat Step 3 and then follow equation B.1 through B.27 to calculate the steady-state values of all the domestic and foreign variables on the real side of the economy.

**Step 6. Estimate the covariance matrix of productivity shocks**

Use the steady-state trade costs computed earlier to solve for time-varying sectoral productivity ($T_{i,s,t}$) that matches the dynamic sectoral trade shares ($\pi_{i,s,t}$) and endowments observed in the data. After that, follow equation B.14 to calculate the corresponding $T_{i,s,t}^*$ every period. The dynamic domestic and foreign sectoral productivity can then be used compute the variance-covariance matrix of productivity shocks ($\Sigma_i$) based on the AR(1) process specified in equation 37.

**Step 7. Extract the coefficient matrices from first order conditions**

Examine the first-order dynamics of the model to extract the coefficient matrices in equation B.33 through B.35. These matrices, capturing the response of consumption and asset returns to productivity shocks, will be used to determine asset positions.

**Step 8. Solve for financial frictions to match observed home bias**

Plug the coefficient matrices obtained in Step 7 and solve for information frictions and transaction costs to minimize the distance between the data and numerical results for both sector- and country-level home bias. This involves plugging the two unknown frictions and coefficient matrices in the portfolio determination equation (B.40) until the inferred asset holdings match home bias observed in the data. Specific steps include:

1) Form the initial guess for asset holdings under no financial frictions using equation B.40:

$$\alpha_0 = [\alpha_{0H,1}...\alpha_{0H,S+1}; \alpha_{0F,1}...\alpha_{0F,S+1}]$$  \hspace{1cm} (B.42)
2) Calculate transaction costs $\tau_0$ under no information frictions to match national home bias. This involves solving for portfolios over a grid of different $\tau$ values using equation B.40 with the initial guess $\alpha_0$, and calculating the resulting home bias until it matches the data under a specific value denoted as $\tau_0$. After that, get the corresponding asset position $\alpha_1$ under $\tau_0$ using equation B.40 again.

3) Compile the initial guesses, including $\tau_0$ for transaction costs, $\alpha_1$ for asset positions, and a vector of zeros for information frictions. Loop over a combination of frictions $\tau$ and $f_s$ until the corresponding asset positions determined by equation B.40 predict the sectoral and national home bias that converge to the data. Consistent with the definition in the empirical section (equation 1), sectoral home bias and national home bias are calculated as

$$ HB_{i,s} = 1 - \frac{\alpha_{F,s}}{1 - MV_{i,s}^{d}} $$

$$ HB_i = 1 - \frac{\sum_{S=1}^{S+1} \alpha_{F,s}}{1 - MV_i^w}, $$

where $MV_{i,s}^{d}$ and $MV_{i,s}^{w}$ represent the share of country $i$ sector $s$ market values ($MV_{i,s}$) in total domestic assets ($\sum_{S=1}^{S+1} MV_{i,s}$) and total sectoral assets ($\sum_I MV_{i,s}$) respectively, while $MV_i^w = \frac{MV_i}{\sum_i MV_i}$ represents the share of country $i$ market values in the global market.

In addition to this baseline strategy, I have tried different initial guesses for financial frictions and greater weights for national than for sectoral home bias when calibrating the frictions to match the data. The quantitative results remain robust under these alternative computation strategies.

\section{Robustness}

\subsection{Empirical Analysis}

Table C.1 presents the robustness check for the relationship between sectoral tradability and sectoral equity home bias. This continuous measure of tradability is based on the sectoral data reported in ISIC Rev. 4 in the International Supply and Use Tables (Int SUTs) from the World Input-Output Database (WIOD). WIOD has a comprehen-
sive coverage of tradable and nontradable industries which line up well with those from the financial datasets (listed in table A.2). I consider both an export-based measure calculated as the ratio of sectoral exports to total sectoral use (EXP/USE bas) and an import-based measure calculated as the ratio of sectoral imports to total sectoral supply (IMP/SUP bas). I calculate the world aggregate exports (imports) as shares of use (supply) added across countries averaged over the sample period 2001-2014 when measuring sectoral tradability. Both measures suggest that sectoral home bias decreases with sectoral tradability, consistent with the baseline finding that home bias is stronger in nontradable sectors.

Table C.2 presents the robustness check for the relationship between time trend and sectoral home bias. The signs of the interaction terms suggest that the decline in home bias over recent years is more pronounced in tradable sectors and in financially-open economies.

C.2 Quantitative Analysis

This section extends the baseline model by adding two important features of globalization: trade imbalances and input-output linkages.

Let $D_{i,t}$ be the trade surplus of country $i$ in year $t$. The aggregate expenditure in country $i$ satisfies

$$X_{i,t} = w_{i,t}L_{i,t} + r_{i,t}K_{i,t} - D_{i,t}. \quad (C.1)$$

The value of $D_{i,t}$ is taken from the World Bank, which reports a country’s external balance on goods and services as shares of GDP. When re-calibrating the model, I follow the steps in B.2, while I replace the balanced-trade condition with equation C.1. The trade surplus/deficit data will be matched by the net asset positions in the solution to the portfolio choice problem. As is predicted by the balance of payments identity, the increase in a country’s holding of net foreign assets equals its trade surplus.

Moreover, I follow the quantitative trade literature including Di Giovanni et al. (2014) and Caliendo and Parro (2015) by adding intermediate inputs and input-output (I-O) linkages to the model. Given intermediate goods from sector $n \in \{1, 2, ... S, N\}$, the new production cost in sector $k$ is

$$c_{i,k} = (r_i^\alpha w_i^{1-\alpha_k})^{\nu_k} (\Pi_n(P_{i,n})^{\gamma_{kn}})^{1-\nu_k}, \quad (C.2)$$

where $\gamma_{kn}$ is the share of input $n$ used for $k$’s production and $1 - \nu_k$ is the weight of
Table C.1: Robustness check for sectoral tradability and sectoral HB

<table>
<thead>
<tr>
<th>Dep. Var: Sectoral HB</th>
<th>Export-based tradability</th>
<th>Import-based tradability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( 1 )</td>
<td>( 2 )</td>
</tr>
<tr>
<td>Tradability</td>
<td>-0.181 ***</td>
<td>-0.194 ***</td>
</tr>
<tr>
<td></td>
<td>( 0.029 )</td>
<td>( 0.021 )</td>
</tr>
<tr>
<td>Country FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Time FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>11,795</td>
<td>11,795</td>
</tr>
<tr>
<td>R²</td>
<td>0.003</td>
<td>0.506</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, standardized coefficients in brackets. ***significant at 1%. The dependent variable is sectoral home bias, the independent variables include tradability based on the sectoral data from the WIOD and country, time fixed effects.

Table C.2: Robustness check for determinants of sectoral HB

<table>
<thead>
<tr>
<th>Dep. Var: Sectoral HB</th>
<th>( 1 )</th>
<th>( 2 )</th>
<th>( 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>-0.006 ***</td>
<td>0.023 ***</td>
<td>-0.004 **</td>
</tr>
<tr>
<td></td>
<td>( 0.001 )</td>
<td>( 0.003 )</td>
<td>( 0.002 )</td>
</tr>
<tr>
<td>Chinn-Ito</td>
<td>27.243 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( 6.044 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year × Chinn-Ito</td>
<td>-0.014 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( 0.003 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tradable dummy</td>
<td>7.583 *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( 4.360 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year × tradable dummy</td>
<td>-0.004 *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( 0.002 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country FE</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Sector FE</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, standardized coefficients in brackets. ***significant at 1%, **significant at 5%, *significant at 10%.
intermediate inputs in sector $k$. I calibrate their values following Di Giovanni et al. (2014), who estimate the parameters using the UNIDO Industrial Statistics Database and the Direct Requirements Table of the U.S.

Table C.3 reports the numerical results under these two extensions. In the scenarios with global imbalances and input-output linkages, asset transaction costs are predicted to play a more significant role in driving home bias. For example, based on the results in columns (4) and (6), sectoral home bias drops to 0.05 and 0.07, which are slightly lower than 0.10 in the baseline model. The difference is more pronounced for national home bias: Extended models predict that home bias drops from 0.46 to about 0.34. Based on this result, asset transaction costs account for approximately a quarter of national home bias. In contrast, the impact of information frictions on both national and sectoral home bias is quantitatively small and similar across different models. Based on the estimates, information frictions explain about 10% and 20% sectoral home bias under trade imbalances and I-O linkages, respectively. These frictions account for between 2% and 10% national home bias, consistent with the result in the baseline case. The similarity of these quantitative findings across different specifications validates the robustness of the numerical results.

Table C.3: Robustness Check for Quantitative Analysis

<table>
<thead>
<tr>
<th>Friction excluded</th>
<th>Observed home bias $\bar{HB}_{i,s}$</th>
<th>Counterfactual home bias $\bar{HB}_{i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>Baseline Imbalances I-O linkages</td>
</tr>
<tr>
<td>$\tau_f$ included</td>
<td>0.29</td>
<td>0.10 0.26 0.05 0.26 0.07 0.23</td>
</tr>
<tr>
<td>$\tau_f$ included</td>
<td>0.46</td>
<td>0.42 0.42 0.34 0.45 0.33 0.41</td>
</tr>
</tbody>
</table>

Note: $\bar{HB}_{i,s}$ denotes the median sector-level home bias, and $\bar{HB}_{i}$ denotes the median country-level home bias. Column (1) reports home bias observed in the data. Columns (2)-(7) list the counterfactual home bias in the baseline quantitative model, in the model incorporating trade imbalances, and in the model featuring input-output linkages, respectively, under the circumstances where transaction costs ($\tau$) and information frictions ($f$) are turned off.